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VIBRATION SIGNAL ANALYSIS TECHNIQUES

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Ohio State University

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The high cost of helicopter maintenance has created a great deal of interest in the monitoring of the condition of helicopter components. In helicopter power trains, which contain both gears and bearings, the use of vibration signals to detect the condition of these gears and bearings has become of increasing interest in recent years.

This research program was initiated to investigate the many means of using vibration signals to detect the condition of mechanical components, with

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particular emphasis on gears and bearings in the helicopter power train. An exhaustive literature search was performed in which specific techniques were identified. Several visits were made to people active in the vibration diagnostics field.

The techniques which were identified as being potentially useful were investigated in detail. The results of this investigation include a presentation of the state of the art of each technique and an analysis via actual helicopter data, test rig data, and a dynamic model simulation. The techniques have been broken down by mathematical function, i.e., time domain and frequency domain, and also by the components being monitored, i.e., gears or bearings. Both mechanically related and pattern recognition techniques are discussed. An extensive reference listing and a listing of companies and agencies active in diagnostics work are included in this report.

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This report was prepared by the Ohio State University Research Foundation under the terms of Contract DAAJ02-72-C-0085. The work reported herein is part of a continuing effort to conduct investigations directed toward advancing the state of the art of diagnostics for Army aircraft.

The object of this effort was to investigate methods of analyzing vibration signals to determine the mechanical condition of gears and bearings in helicopter power trains. The effort included an exhaustive literature search and discussions with people active in the field of vibration diagnostics.

The objective of this effort was achieved inasmuch as the report that was compiled includes an extensive identification and discussion of vibration signal analysis techniques that may be useful for diagnostic purposes. A proposed method of ranking various techniques is also included. A quantitative evaluation of the techniques was conducted, the results of which are available from this Directorate to other Government agencies.

This report can serve to define possible techniques for future Army research effort. It can also provide useful information for firms interested in conducting research in vibration analysis techniques for diagnosing the condition of mechanical components.

The tecnical monitor for this contract was Mr. G. William Hogg, Military Operations Technology Division.

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VIBRATION SIGNAL ANALYSIS TECHNIQUES

Final Report

By

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FORT EUSTIS, VIRGINIA

ABSTRACT

The high cost of helicopter maintenance has created a great deal of interest in the monitoring of the condition of helicopter components. In helicopter power trains, which contain both gears and bearings, the use of vibration signals to detect the condition of these gears and bearings has become of increasing interest in recent years.

This research program was initiated to investigate the many means of using vibration signals to detect the condition of mechanical components, with particular emphasis being placed on gears and bearings in the helicopter power train. An exhaustive literature search was performed in which specific techniques were identified. Several visits were made to people active in the vibration diagnostics field.

The techniques which were identified as being potentially useful were investigated in detail. The results of this investigation include a presentation of the state of the art of each technique and analysis via actual helicopter data, test rig data, and a dynamic model simulation. The techniques have been broken down by mathematical function, (time domain and frequency domain) and also by the components being monitored (gear or bearing). Both mechanically related and pattern recognition techniques are discussed. An extensive reference listing and a listing of companies and agencies active in diagnostics work are included in this report.

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LIST OF SYMBOLS

BW	bandwidth, Hz
d	diameter of bearing rolling element, in.
D	bearing pitch diameter, in.
f	frequency, Hz
f_b	bearing ball-pass frequency, Hz
f_{br}	bearing ball resonance frequency, Hz
f_c	bearing cage pass frequency, Hz
f_{gm}	gear mesh frequency, Hz
f_{ir}	bearing inner race frequency, Hz
f_{or}	bearing outer race frequency, Hz
f_{rr}	bearing race resonance, Hz
I	moment of inertia, $in.^4$
j	$\sqrt{-1}$
N	operating speed, rpm
$Q_{xx}(F)$	autospectral correlation
$Q_{xy}(F)$	cross-spectral correlation
$R_{xx}(\tau)$	autocorrelation
$R_{xy}(\tau)$	cross correlation
$S_x(f)$	power spectral density
$S_{xy}(f)$	cross power spectral density
t	time, sec
$\gamma(f)$	coherence function
μ_x	mean value
ω	frequency, rad/sec
β	contact angle, deg

ρ	density, lb/ft^3
σ_x	variance
φ	phase angle, deg
ψ_x^2	mean squared value

INTRODUCTION

This section includes a discussion of the objectives of this program, the reasons for it, a review of the work performed, and the significant results. The work was performed by The Ohio State University from July 1, 1972 to June 15, 1973.

OBJECTIVE

The primary objective of this program was to perform a detailed study of all known data analysis and data reduction techniques which might be applicable for use in performing vibration diagnostics on helicopter power train components. In this context, power train components will refer primarily to the gears and bearings in the power train and not directly to housings and supports for these components.

As a portion of this study, it was necessary to perform a comprehensive literature search to identify techniques which have been used for diagnostics and also to identify those individuals, companies, and Government agencies who have utilized vibration diagnostics techniques.

DIAGNOSTIC BACKGROUND

Over the past 20 years there has been a growing interest in machine vibration monitoring. Much of this work has been related strictly to measuring overall vibration levels in order to detect the condition of a bearing, gear or other moving part. However, in recent years there has been a specific interest in utilizing vibration signatures to diagnose operational problems and the ensuing failure of machine components. These vibration signatures relate specific vibration signal characteristics (normally either in the frequency or time domain) to specific moving parts of the machine. Changes in these signal characteristics are then used to determine some change in the mechanical condition of specific components.

The ability to diagnose the condition of mechanical parts may be beneficial to anyone who may incur the dangers of catastrophic failures or who must perform periodic maintenance on a machine. Diagnosis of parts could reduce catastrophic failures by detecting incipient failures before they occur. In the case of the helicopter, this ability could save lives and save very expensive machines from total destruction. However, the prime financial savings are likely to be rendered in application to on-condition maintenance programs which would replace parts when detected as faulty by the diagnostic system. An increase could be achieved in the time between overhauls and thus result in an overall increase in the operating efficiency. The ability to prognosticate the lives of parts would also provide further maintenance advantages. A comprehensive study of potential maintenance cost savings on helicopters, if a reliable diagnostic system were implemented, has been reported by Northrop Corporation.[1]

PROGRAM CONDUCT

This program was divided into four separate tasks:

Task 1. Survey of vibration signal analysis techniques.

Task 2. Development of a simplified dynamic model for use in evaluating techniques.

Task 3. Analysis of vibration data analysis techniques.

Task 4. Final evaluation and recommendations.

During Task 1, a comprehensive literature search was performed to obtain papers, reports and other information on diagnostic techniques. The facilities of The Ohio State University Libraries were used for a large portion of this search. Also NASA and DDC searches were performed. Approximately 400 papers, reports, and articles were found in these searches. Companies who were involved in diagnostics work were contacted in this task; these contacts were made by phone, mail, and personal visits. A listing of the companies and individuals who were contacted is given in Appendix I. Based on the literature search and the company contacts, a state-of-the-art description of the various diagnostic methods which seem appropriate for helicopter transmissions was compiled.

Task 2 included analysis to establish the types of mechanical failures in helicopter transmissions that are likely to influence vibration signals. A simplified dynamic model for bearing vibrations was then developed for use in evaluating diagnostic techniques. This model utilized information from the failure analysis to ascertain input forces.

In Task 3 of this study, the various techniques uncovered in Task 1 were evaluated in several ways. First, the techniques were evaluated in light of results of other investigations found in the literature. Second, the dynamic model developed in Task 2 was used to evaluate bearing diagnostic techniques. Third, a small test rig was built to test specific bearing diagnostic techniques. Finally, helicopter data from the UH-1 AIDAPS Test Bed Program[2,3] was used to identify the characteristics of typical vibration signals from helicopters, and this data was used to evaluate the different techniques.

A final evaluation of all techniques was made in Task 4. Included in this evaluation were the ease of application of the technique, accuracy, repeatability, amount of testing required, and ability to diagnose and also to prognosticate on the condition of helicopter components (on a line-replaceable unit or component basis).

REPORT CONTENTS

This report is divided into seven sections: INTRODUCTION, PHYSICAL PHENOMENA, MATHEMATICAL TECHNIQUES, GENERAL DIAGNOSTIC PROCEDURES,

SPECIFIC TECHNIQUES, EVALUATION OF TECHNIQUES, GENERAL CONCLUSIONS, and RECOMMENDATIONS. The report has six appendixes. A short description of the contents of each section and the six appendixes is given below.

INTRODUCTION - See above.

PHYSICAL PHENOMENA - The physical phenomena which are related to bearing and gear failures are discussed. Included are treatments of the types of vibrations generated by faults and a brief discussion of the vibration transmission paths located between the fault and the vibration transducer.

MATHEMATICAL TECHNIQUES - Mathematical techniques used for analyzing the vibration signal are discussed, with the primary emphasis placed on time domain and frequency domain analysis techniques. However, statistical techniques are also included. The discussion of digital methods of performing the standard analysis techniques is also presented.

GENERAL DIAGNOSTIC PROCEDURES - This section treats the generalized approaches to the diagnostics problem. Two basic approaches are discussed: (1) the determination of discriminants based on the mechanical phenomena related to a given failure mode, and (2) the identification of discriminations which are obtained by so-called pattern recognition techniques.

SPECIFIC TECHNIQUES - The state of the art of many of the specific diagnostic techniques which have been used for rotating systems containing gears and rolling element bearings is presented. The discussion includes information on vendors, users, and specific application as well as processing techniques and hardware used.

EVALUATION OF TECHNIQUES - An evaluation of the techniques discussed is performed. The test rig data, bearing model data, and test bed data are used in the evaluation. Also presented here are discussions of the typical helicopter data which was gathered in the test bed program.

GENERAL CONCLUSIONS - The generalized problem of vibration diagnostics in helicopters is discussed and general conclusions are presented.

RECOMMENDATIONS - A comprehensive set of recommendations are presented for future work in the area of vibration diagnostics with application to the helicopter power train.

APPENDIX I - A list of all individuals and companies contacted during the course of this program; also a brief discussion of the results of each contact.

APPENDIX II - A glossary of terms used in the identification and prediction of mechanical failure as produced by the mechanical failures prevention group.

APPENDIX III - A description of data tapes dubbed from the AIDAPS Test Bed Program data.

APPENDIX IV - A listing of some of the frequencies associated with particular components of a UH-1D.

APPENDIX V - A report on an analysis of the data as described in Appendix II that was performed by Scope Electronics, Inc.

APPENDIX VI - A technique for determining a numberical evaluation of a diagnostic system relative to others is shown.

PHYSICAL PHENOMENA

The ability to apply any vibration signal analysis technique as a diagnostic tool is predicated on the existence of characteristic vibration signals. These must be produced or caused in some manner by the system component being monitored. Because of the characteristic frequencies produced by gears and bearings, the prime emphasis of diagnostic systems to be used on power trains has been directed toward them.

A brief discussion of physical phenomena as related to gears and bearings as well as a general discussion and description of a gear and bearing is given. Typical faults that might be encountered are enumerated, and finally, the typical frequencies that might be encountered are described.

The last portion of this section discusses transmission paths. It is usually quite difficult to place a sensor directly at the source of a vibration signal. This signal must instead pass through housings, mountings, structural members, etc., to reach the sensor. The path along which the signal must travel will have an effect on the final sensor reading. The discussion includes a description of the kind of effects the transmission path might have on the signal as well as the common manners of analyzing these effects.

BEARINGS

By definition, bearings are the elements used in rotating mechanical systems to permit relative and controlled motion between two loaded members. Based on their wide usage and basic characteristics, bearings are a prime candidate for application of vibration diagnostic systems.

In categorizing bearings, they may first be broken into two broad groupings: plain bearings and rolling-element bearings. Plain bearings operate with a sliding motion between two surfaces, generally supported by an elastohydrodynamic film. Since this type of bearing is not prevalent on helicopters, this study has dealt primarily with rolling-element rather than plain bearings.

Rolling-element bearings, as their name suggests, permit motion through relative rotation of their elements. In describing the major types of rolling-element bearings, they are first broken down according to the shape of the rolling element, i.e., ball or roller. They could also be classified as to direction of load, i.e., radial, angular, or thrust.

Figure 1 shows a diagram of a typical radial bearing. There are four major components:

<u>Inner race</u>: This component is mounted on the shaft and rotates with it. It contains a track for the rolling elements to run in.

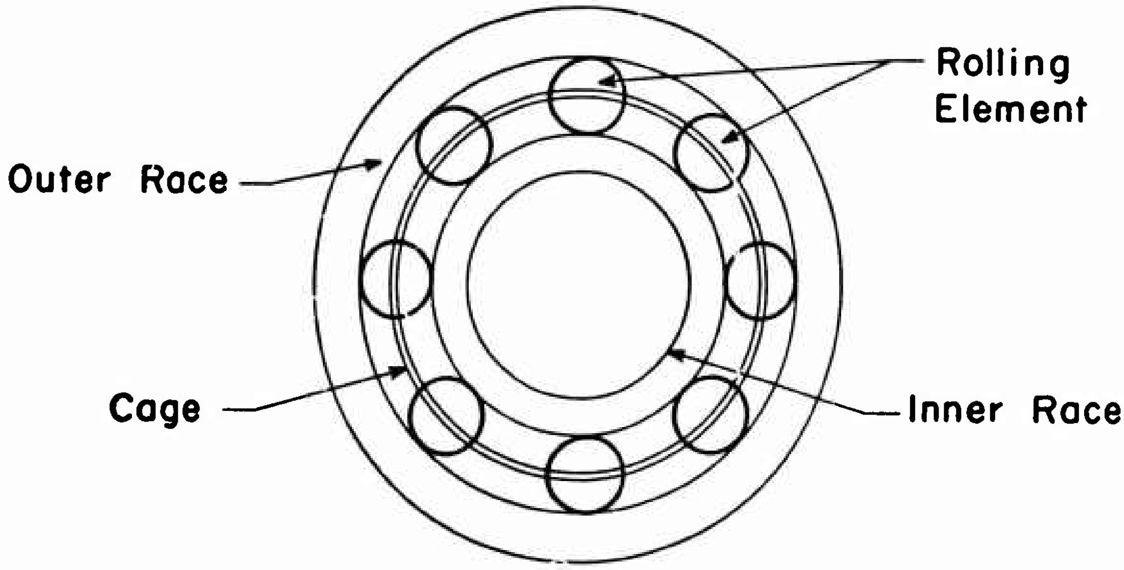


Figure 1. Sketch of Typical Rolling-Element Bearing.

Outer race: This component is mounted in a housing and usually remains fixed. It also contains a track for the rolling elements.

Rolling element: These elements rotate between the races.

Cage (Retainer): This component connects the rolling elements and keeps an equal spacing between them. It rotates about the shaft.

Further definitions of parameters which might be needed are:

Pitch diameter: Distance from the center of the bearing to the center of the rolling element.

Contact angle: The angle between the direction of loading force and the normal to the shaft.

As shown in Figure 2, five general types of ball bearings can be described:[4]

Deep groove or Conrad: Standard type of single-row, radial loaded bearing.

Angular contact: Used when capability to carry thrust as well as radial load is desired. They are easy to disassemble.

Self-aligning: Has outer race groove ground to a spherical shape to allow balls to seat themselves, thus providing alignment.

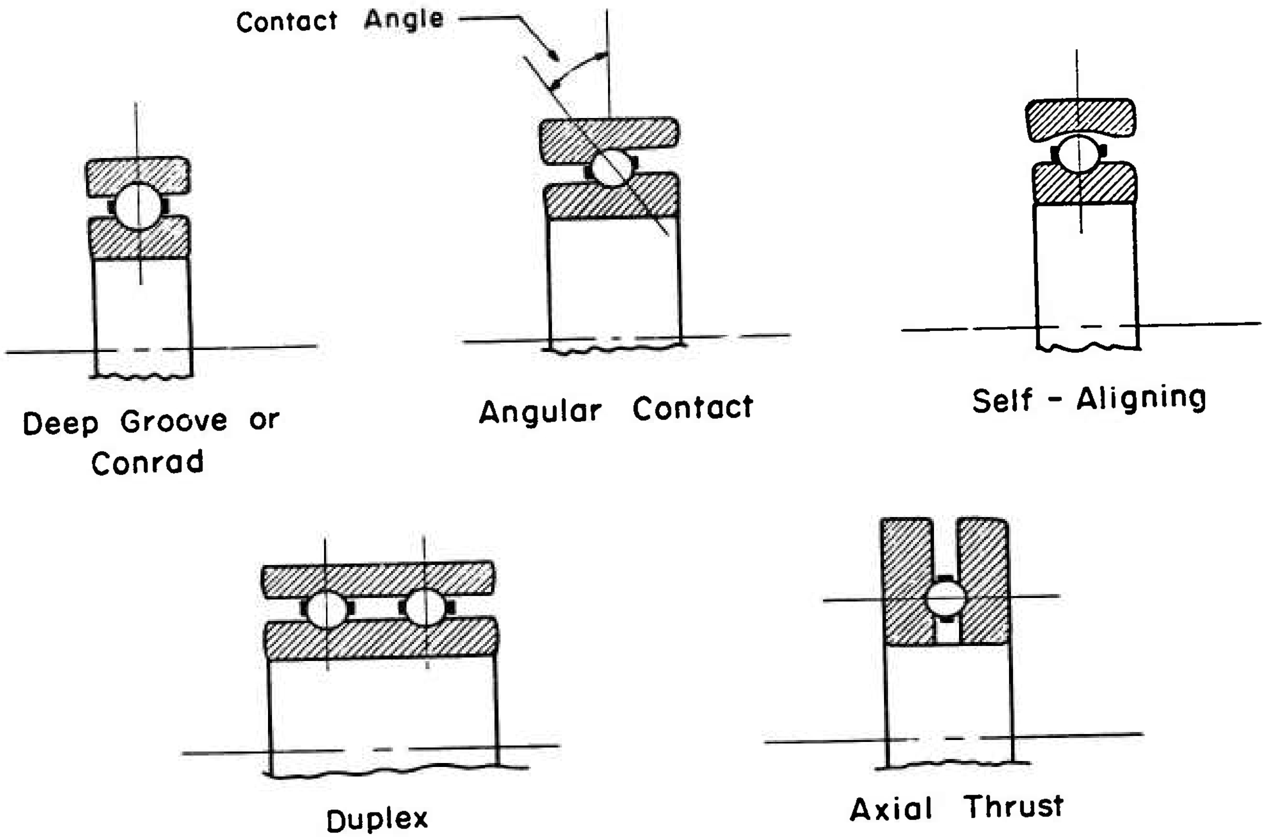


Figure 2. General Types of Ball Bearings.

Duplex: Refers to bearings manufactured with two sets of rolling elements.

Ball thrust: Designed to handle thrust loads only.

Roller bearings differ from ball bearings in the shape of the rolling element. As shown in Figure 3, four major classes can be discussed:[5]

Cylindrical: Rolling elements are cylinders. Used with high-speed radial loads where more contact area is desired than that available with ball bearings.

Tapered: Rolling element is a tapered cylinder. Can handle thrust as well as radial load.

Spherical: Rolling element has rounded contour. Can be used with thrust as well as radial load.

Needle: Cylindrical rolling element is used without any retainer. Usable in low-speed, high-load operations; sometimes used without inner race.

A typical helicopter will contain a wide variety of the various types of rolling element bearings.

Typical Bearing Faults

There are many bearing faults which are potential candidates for diagnosis. These faults fall into the general category of surface failures, which can be either fatigue or nonfatigue initiated.[6] In the case of nonfatigue initiated faults, the ultimate destruction is often the result of a fatigue failure induced by the nonfatigue failure rather than by bearing operation.

Contact fatigue failures take one of two forms:

Spalling (Flaking): Small flakes of the surface are broken off. These flakes are often of elliptical shape. Continued operation of the bearing can cause this flaking to occur over the entire bearing surface.

Pitting: Small pits are formed on the bearing surfaces. These do not propagate but are local. This phenomenon can lead to spalling.

Contact fatigue failures may be found on any bearing surface upon which contact between two components of the bearing occurs.

Nonfatigue failures may take a variety of forms. The following list

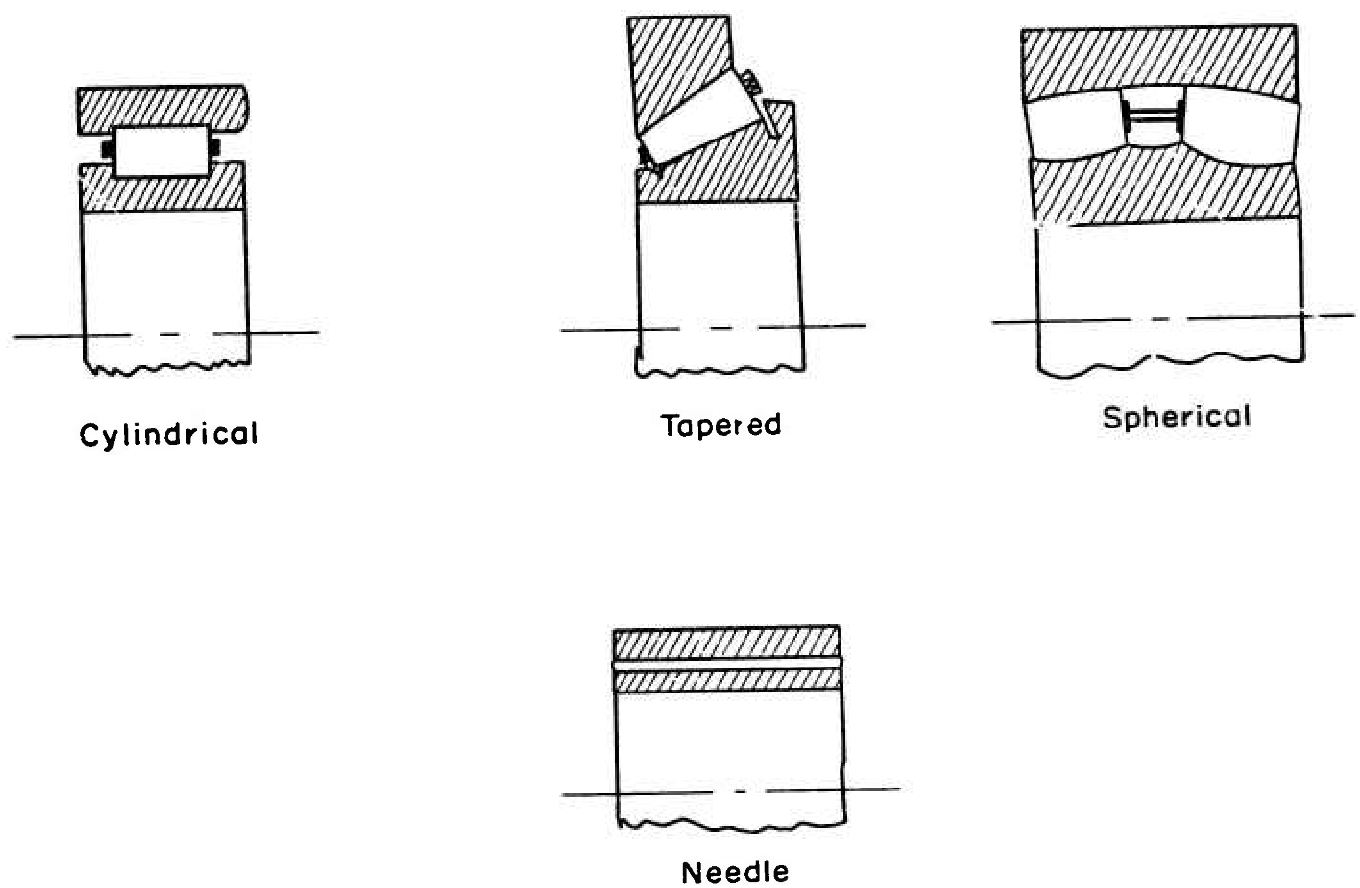


Figure 3. General Types of Roller Bearings.

contains the most common failure modes with the names that appear in general usage.

Mechanical damage: Faults are often introduced in either manufacturing or installation. They may be seen as dents, nicks, scratches, etc., which are not a result of bearing operation.

Foreign material: The introduction of foreign material, e.g., dirt or metal chips, into the contacting surfaces can cause a grinding phenomenon to occur. The contacting surfaces will exhibit a dull or matte finish.

True brinelling: This is an indentation which will occur in a race due to plastic flow of the metal. The cause is high stress levels induced during operation, e.g., by shock loading. Grinding marks may be discernible.

False brinelling (Fretting): Indentations which may be seen as the result of fretting corrosion. This may be caused by vibration or small amplitude motion of bearing elements when they are in static contact.

Electrical pitting: An "arc-welding" effect which occurs when an electric current is passed through a bearing. Annealing of surfaces may occur.

Corrosion: Ordinary oxidation corrosion (rusting) which can be caused by the introduction of moisture or oil contaminants into the bearing.

Creeping: This is a relative motion between the inner race and shaft.

Skidding, scuffing, or scoring: Scratching of the bearing surface caused by sliding rather than rolling of the rolling elements. Often, the cause is a breakdown of the lubrication film.

Wear: General loss of material due to prolonged operation.

Bearing failures may occur in any of the variety of forms listed. On a bearing the failures can be labeled as either discrete or general. A discrete failure is one which extends over a small portion of a bearing or on a small number of the rolling elements. A general failure occurs over a large portion of the bearing surface. This distinction is often made in describing the capabilities of diagnostic systems.

Characteristic Rotational Frequencies

One of the properties of bearings which make diagnostic systems usable is the characteristic rotational frequencies which they produce. Based on the position of a given fault, i.e., race or ball, impacts and vibrations will be produced at frequencies which are a function of the component and the speed of rotation. For example, if a race is scratched, every time a rolling element makes contact with the scratch an impact will be transmitted through the bearing. This impact will repeat itself as a function of bearing rotation. Spectral identification at these characteristic frequencies is the basis for many diagnostic systems.

The following parameters are required for calculation of these characteristic rotational frequencies:

d = diameter of rolling element, in.
D = bearing pitch diameter, in.
β = contact angle, deg
n = number of rolling elements
N = operating speed, rpm

Using these parameters and a kinematic analysis of the bearing action, the following equations may be found:[7]

Outer race frequency:

$$f_{or} = \frac{n}{2} \cdot \frac{N}{60}\left(1 - \frac{d}{D}\cos\beta\right), \quad \text{Hz} \tag{1}$$

Inner race frequency:

$$f_{ir} = \frac{n}{2} \cdot \frac{N}{60}\left(1 + \frac{d}{D}\cos\beta\right), \quad \text{Hz} \tag{2}$$

Rolling element (ball or roller) frequency:

$$f_b = \frac{D}{d} \cdot \frac{N}{60}\left(1 - \left(\frac{d}{D}\right)^2 \cos^2\beta\right), \quad \text{Hz} \tag{3}$$

Cage frequency:

$$f_c = \frac{N}{120}\left(1 - \frac{d}{D}\cos\beta\right), \quad \text{Hz} \tag{4}$$

As an example of the values which might be found for these frequencies in a typical bearing, the calculations were performed for a Norma-Hoffman L-25, which is a 2-inch, single-row, angular contact bearing. The parameters for this bearing are: $r = 0.15625$ in., $D = 1.540$ in., $\beta = 15$ deg, $n = 12$, and $N = 1750$ rpm. The frequencies calculated are: $f_{or} = 140.7$ Hz, $f_{ir} = 209.3$ Hz, $f_b = 138.2$ Hz, $f_c = 11.7$ Hz. It should be noted that as well as these fundamental characteristic frequencies, harmonics (or multiples) may also be generated by vibration due to faults.

Resonant Frequencies

The various "pass" or rotational frequencies discussed previously are a result of the rotation of the bearing causing periodic impacting. This impacting can also induce other vibrations to occur in the bearing. Structural resonances may be excited, thus causing "ringing," which is the continuum vibration response of the bearing structure. Both races and the rolling elements can exhibit this "ringing." It is characterized by an exponentially decaying, high-frequency oscillation. The "ring" will reappear periodically at the "pass" frequency corresponding to the fault which excites it. "Ringing" or resonant frequencies are structural characteristics. Their frequency of oscillation does not depend on the speed of rotation of the bearing. Figure 4 shows a sketch of a typical "ringing" response.

The rolling element resonance is one of the typical resonances which may be excited as the rolling element pulsates as a rigid body due to the impact. The frequency of free resonance of a ball may be calculated by[8]

$$f_{br} = \frac{0.848}{2r} \frac{E}{2\rho} \tag{5}$$

where E = modulus of elasticity, psi
ρ = density of rolling element, slugs/in.^{3}

For the bearing used as the example before, the ball resonance frequency is $f_{br} = 387{,}500$ Hz. The races will also exhibit resonant characteristics. The equation describing their characteristic free resonant frequencies is[9]

$$f_{rr} = \frac{k(k^2 - 1)}{2\pi \sqrt{k^2 + 1}} \frac{1}{a^2}\sqrt{\frac{EI}{m}} \tag{6}$$

where k = order of the resonance
a = radius to the neutral axis, in.
I = moment of inertia of cross section, in.^{4}
m = mass of race per linear inch, slugs/in.

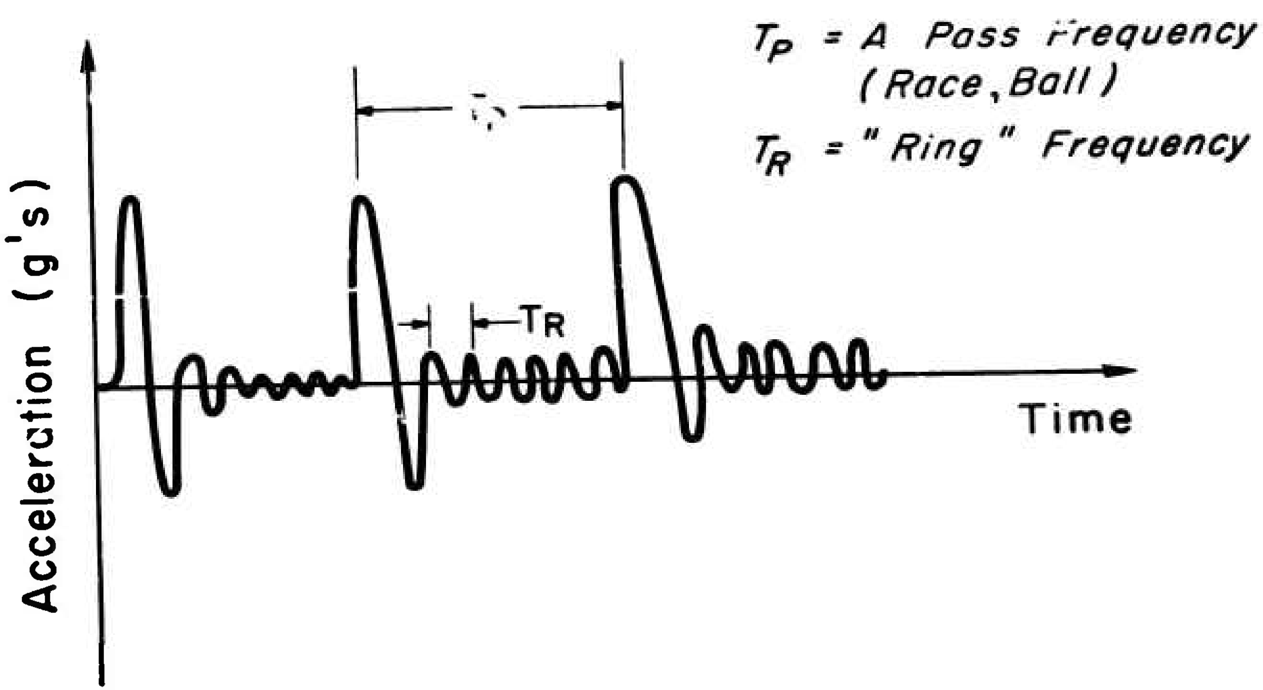


Figure 4. Typical "Ringing" Response.

A given structure will have an infinite number of resonant frequencies, i.e., second resonance, third resonance, etc. The number of the resonance is referred to as its order. As seen from Equation (6), the orders of the resonances do not vary linearly as do the harmonics of the pass frequencies.

For the sample bearing, Table I gives a list of the race resonances for the inner and outer race.

TABLE I. RACE RESONANCES AS CALCULATED FOR BEARING

k(order)	f(frequency) (Hz)
Inner race	
2	3,940
3	11,140
4	21,360
5	34,540
6	50,660
Outer race	
2	9,740
3	27,560
4	52,830

In the equations presented, the free or unmounted resonances were found. These represent the frequency of oscillation if the ball or race is standing alone without the rest of the bearing. This is not the case in operation since mounting will change the exact frequency of "ringing". However, these frequencies will remain near the frequencies calculated for the free case.

GEARS

Gears are machine elements which are used to transfer power between shafts while retaining fixed speed ratios. They can be used to change speed or torques while operating efficiently (up to 98%). Pitch-line speeds of up to 40,000 ft/min are attainable, and an almost unlimited size permits a greater load capacity than other power transmission elements.

Based on these characteristics, gears appear in a wide variety of drive systems and are used almost exclusively as the speed change elements in the drive systems of helicopters. There are a variety of gear types used: spur, bevel, helical, etc. A typical helicopter will contain spur gears and spiral bevel gears as well as planetary systems for speed reduction.

Due to their wide usage and rotational characteristics, gears, along with bearings, are prime candidates for diagnostic evaluation. Also, their criticality for flight safety has made gearing an important maintenance item and a prime target for maintenance cost reductions.

Typical Faults

In gearing, there are number of faults for which diagnostics are hoped to be useful. A listing of these includes:

Wear: A surface phenomenon in which layers of metal are removed or "worn away" more or less uniformly from regions of the contacting surfaces of the gear teeth.

Pitting: A surface fatigue failure which occurs when the endurance limit of the material is exceeded. A failure of this nature depends on the surface contact stress and the number of stress cycles, and results in small surface fatigue cracks which propagate about the surface, causing the loss of material and the formation of pits.

Spalling: Similar to pitting except that material is removed in larger areas.

Scoring: Rapid wear resulting from a failure of the oil film caused by overheating of the mesh, permitting metal-to-metal contact. This contact produces alternate welding and tearing, which removes metal rapidly from the tooth surfaces.

Fracture: Failure caused by breakage of a whole tooth or a substantial portion of a tooth. This failure can result from overload, or more commonly, by cyclic stressing of the gear tooth beyond the endurance limit of the material.

Plastic flow: Cold working of the tooth surfaces, caused by high contact stresses and the rolling and sliding action of the mesh. It is a surface deformation resulting from the yielding of the surface and subsurface material and is usually associated with softer gear materials.[10]

Characteristic Rotational Frequencies

The primary rotational frequency associated with geared systems is the gear mesh frequency. It is a function of the number of teeth and the rotational speed. The frequency corresponds to the motion induced by the consecutive meshing of the teeth. The definition of frequency is

$$f_{gm} = \frac{N}{60} \cdot n, \quad \text{Hz} \tag{7}$$

where N = shaft speed, rpm
n = number of teeth

If a fault occurs on a tooth surface, a vibration will be induced at this frequency.

Along with the meshing frequency, mesh frequency harmonics and sidebands may occur.

Sidebanding

Sidebanding is a phenomenon which is induced by modulation of a signal, either by amplitude modulation (AM) or by frequency modulation (FM). It is a common occurrence in geared systems. Before discussing the phenomenon in more detail with respect to gearing, a brief mathematical description follows.

A sinusoidal signal may be represented in general form by the equation

$$f(t) = A \cos(2\pi f_c t + \varphi) \tag{8}$$

where $f(t)$ = signal as a function of time
A = amplitude of signal
f_c = carrier frequency, Hz
φ = phase angle, rad

In the case of amplitude modulation of the signal, A becomes a function of time. In the case of frequency modulation, φ becomes a function of time.

For a typical AM signal, we can describe the amplitude modulation as

$$A(t) = K(1 + m \cdot \cos 2\pi f_m t) \tag{9}$$

where K = constant
f_m = modulating frequency, Hz
m = fractional extent to which the amplitude is modulated

Thus,

$$f(t) = K(1 + m \cdot \cos 2\pi f_m t)\cos(2\pi f_c t + \varphi) \tag{10}$$

This expression may be expanded by the laws of trigonometry.

$$f(t) = k \left\{ \cos(2\pi f_c t + \varphi) + \frac{m}{2} \cdot \cos[2\pi(f_c - f_m)t + \varphi] + \frac{m}{2} \cdot \cos[2\pi(f_c + f_m)t + \varphi] \right\} \quad (11)$$

Figure 5 shows spectra of the signal before and after modulation. The two new spikes are the sidebands.

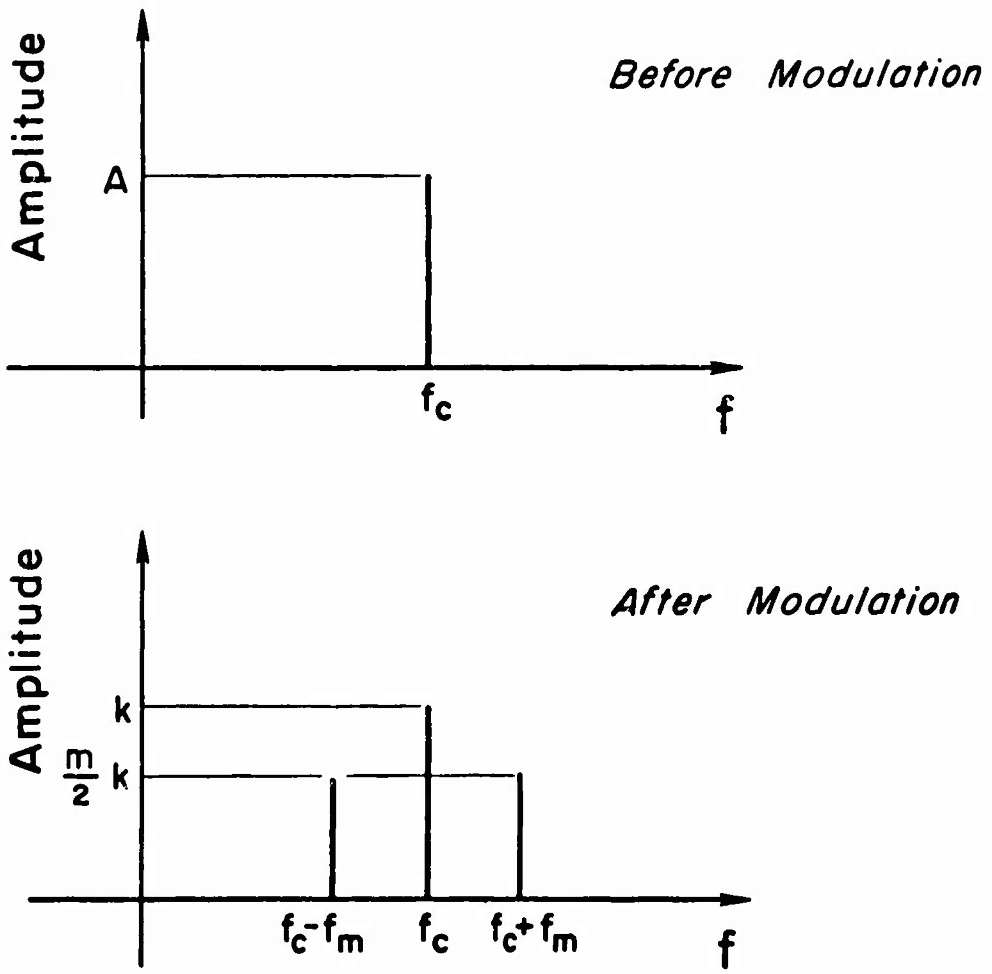


Figure 5. Spectra of a Typical Sinusoidal Signal Before and After Modulation.

This type of analysis (with trigonometric expansion) for amplitude modulation may be performed for any modulating time function by simply expanding

the time function in a Fourier series. Sidebands will occur at the carrier frequency plus or minus the modulation frequency.

For a typical FM signal, we can describe the phase angle as a function of time by

$$\Phi(t) = \beta \sin 2f_m t \tag{12}$$

where f_m = modulating frequency
β = modulation index (represents the maximum phase shift exhibited by the carrier frequency during a cycle).

Thus,

$$f(t) = \cos(2\pi f_c t + \beta \sin 2f_m t) \tag{13}$$

This expression may be expanded to give

$$\begin{aligned} f(t) = {} & J_0(\beta) \cos 2\pi f_c t - J_1(\beta)\{\cos[2\pi(f_c - f_m)t] - \\ & \cos[2\pi(f_c + f_m)t]\} + J_2(\beta)\{\cos[2\pi(f_c - 2f_m)t] + \\ & \cos[2\pi(f_c + 2f_m)t]\} \ldots \\ & + (-1)^k J_k(\beta)\{\cos[2\pi(f_c - kf_m)t] \\ & + (-1)^k \cos[2\pi(f_c + kf_m)t]\} \end{aligned} \tag{14}$$

where $J_k(\beta)$ = kth order Bessel function of β
k goes from 0 to ∞

It should be noted that the amplitudes of both the carrier and sideband frequency components are functions of β. And since $J_0(\beta)$ is always less than one, the amplitude associated with the carrier frequency is lessened by modulation as contrasted to the AM case. An infinite number of sidebands is possible.[11]

Modulations in gearing usually occur with the mesh frequency as the carrier and shaft frequency or one of its multiples as the modulating frequency. An example of a mode of amplitude modulation would occur in a gear mesh having an eccentric gear. By periodically forcing the teeth into the mesh, a cyclic loading pattern occurs, with a minimum and maximum mesh force occurring once per shaft rotation. As the eccentricity increases, the sideband amplitudes will increase.

Frequency modulation may be present as the result of errors in gear

manufacture. If there is a spacing error in the cutting tool, the tooth spacing on the gear could change as a function of the rotation, thus producing a frequency modulation.

Modulation effects appear to occur with a wide variety of gearing faults. The exact physical relationship of the fault to the modulation is not known, but it has been observed in experiments by many investigators.

SIGNAL TRANSMISSION PATHS

Both good and faulty gears and bearings generate forces at their moving interfaces which are, in turn, transmitted through the helicopter structure to a given transducer location. Since the transducers are rarely located directly at the fault location, the structural dynamics between the force generation point and the transducer location are of utmost importance. This is particularly true when data is being taken at more than one operating speed or where speed cannot be held constant.

The effects that the structure has on the transducer output readings and means of analyzing helicopter structures in order to predict the instrument system's response under different load and speed conditions will be discussed briefly.

Mechanical Transfer Function

As with electrical systems, mechanical system models may be expressed in the form of transfer functions. A very simple example of this is shown with the simple single-degree-of-freedom system shown in Figure 6, where F is the input and Y is the system response. The parameters are

k = spring constant, lb/in.
c = damping coefficient, lb-sec/in.
m = system mass, lb-sec^2/in.
$f(t)$ = input force, lb
y = output displacement, in.

When Newton's Law is applied, the following differential equation results:

$$\frac{md^2y}{dt^2} + c\,\frac{dy}{dt} + ky = f(t) \tag{15}$$

By Laplace transforming the above equation with zero initial conditions, we get

$$(ms^2 + cs + k)Y(s) = F(s) \tag{16}$$

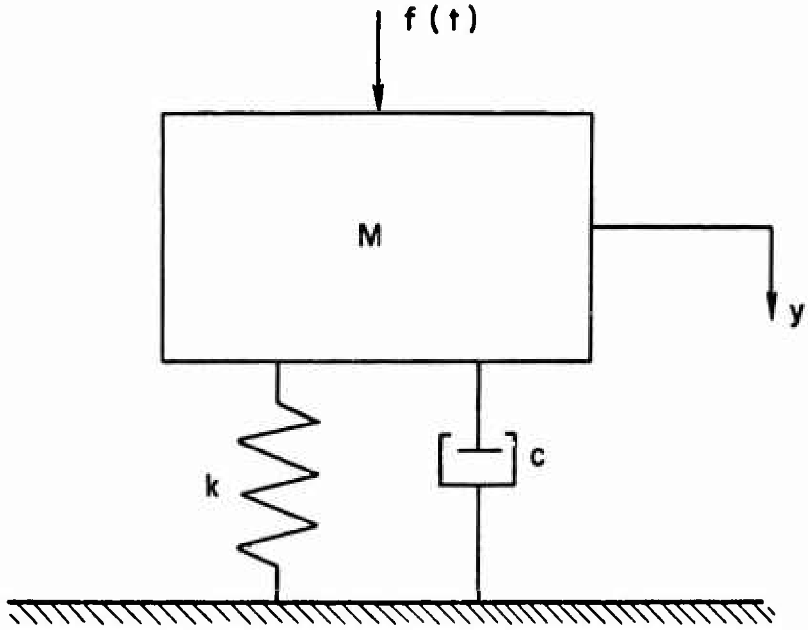


Figure 6. Sample Single-Degree-of-Freedom Spring Mass Damper System.

The transfer function between the input and output is then

$$\frac{Y(s)}{F(s)} = \frac{1}{ms^2 + cs + k} \tag{17}$$

which is a second-order transfer function, which, when written in standard form is

$$\frac{Y(s)}{F(s)} = \frac{K}{\frac{s^2}{\omega_n^2} + \frac{2\rho}{\omega_n} s + 1} \tag{18}$$

$K = \frac{1}{k}$ = static sensitivity

$\omega_n = \frac{k}{m}$ = natural frequency rad/sec

$\rho = \frac{c}{2\sqrt{km}}$ = damping ratio

Another means of expressing the above transfer function is with frequency response techniques where the force f(t) is a sinusoidal force $f(t) = F \sin \omega t$. This can be easily evaluated by making the substitution $s = j\omega$ ($j = \sqrt{-1}$) into the transfer function and then evaluating the amplitude ratio $\left|\frac{Y}{F}\right|$ and the phase angle φ, between Y and F. This would result in a frequency response plot shown in Figure 7.

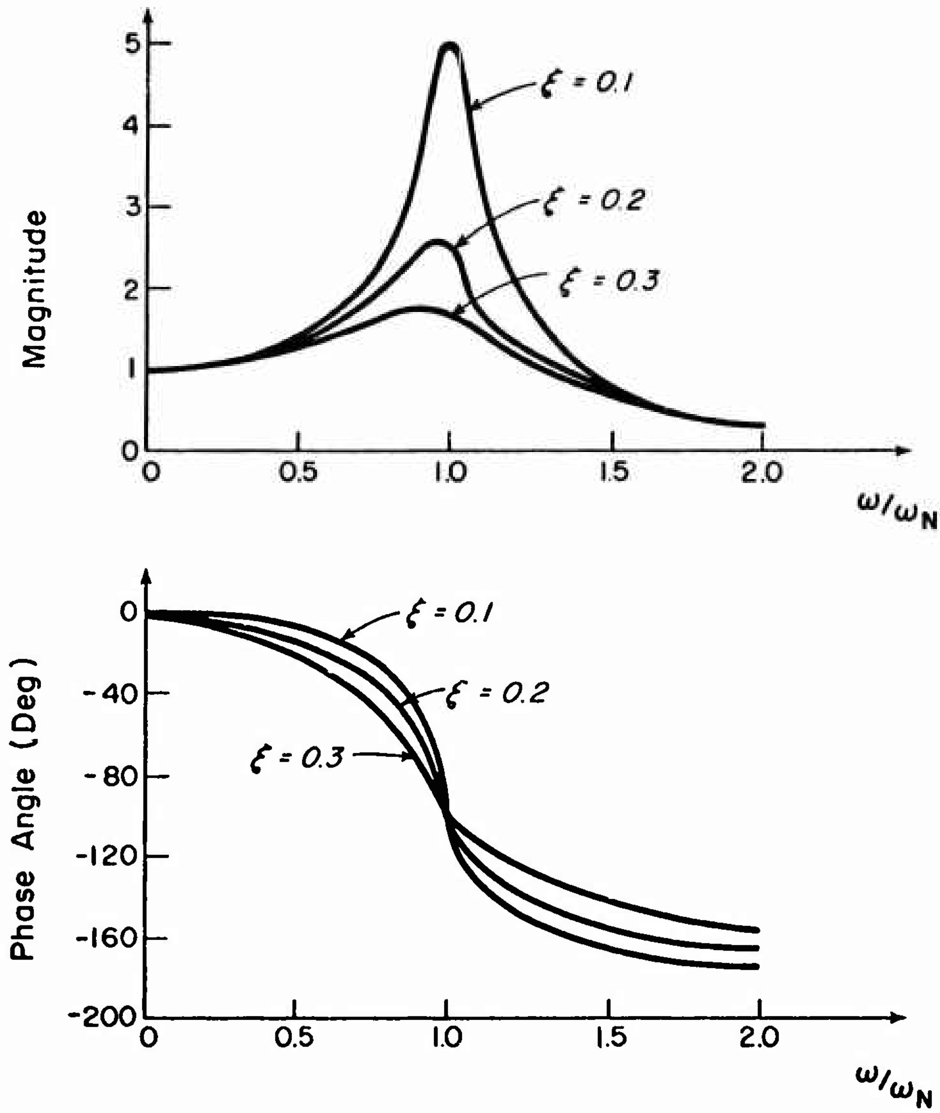


Figure 7. Frequency Response of Second-Order System.

The shape of the above curve is a function of the damping ratio, with the high-amplitude resonant peak increasing as the damping ratio is decreased.

In more complex systems, such as in machine tools, construction equipment, or helicopter transmissions, similar transfer functions may be obtained between forces and motions at any location on the structure. The transfer function will be considerably more complex than the example above and will be more difficult to examine analytically. Also, for a given input force, there may be several paths which the signal may follow to arrive at the output motion, thus further complicating the form of the transfer function.

The frequency response plot of the simple second-order system can be used in an explanation of the importance of the dynamics of the machine element being tested. Since most force inputs from gears and bearings are periodic, they can be expressed as a series of summations of sinusoidal terms (Fourier series) as shown below.

$$f(t) = F_1 \sin(\omega_1 t + \varphi_1) + F_2 \sin(\omega_2 t + \varphi_2) + F_3 \sin(\omega_3 t + \varphi_3) + \ldots \tag{19}$$

The output will be of the form

$$Y(t) = Y_1 \sin(\omega_1 t + \varphi_1 + \varphi_1') + Y_2 \sin(\omega_2 t + \varphi_2 + \varphi_2') + Y_3 \sin(\omega_3 t + \varphi_3 + \varphi_3') + \ldots \tag{20}$$

where $\frac{Y_1}{F_1}$ is the amplitude ratio at ω_1 and φ_1 is the phase angle at ω_1, etc., for ω_2, ω_3,.... One can see that the output amplitudes Y_1, Y_2, Y_3 are strongly dependent upon the frequency response shape. If one of the frequencies should be near the natural frequency, a large amplification may occur. In physical structures, which are typically lightly damped, this amplification may be a factor of 100 or more. In more complex structures, amplitude reduction by a factor of 100 is not uncommon at anti-resonant frequencies. With structural magnification effects of this order, it becomes apparent that the path from the signal source can be very critical and can greatly affect the transducer output.

These large variations in amplitude become increasingly apparent when speed changes occur in the subject machine. Frequency normalization becomes inaccurate if the resonances are near one of the source frequencies. Changes in speed of a constant force input could greatly change the output amplitude as it moves through the resonant peaks. Often the effect of speed changes is eliminated by taking data at only a single speed. This procedure works out well if this is possible. However, speeds must be carefully watched since speed changes of 2-5% can cause amplitude ratio changes of one to two orders of magnitude.

Sinusoidal transfer functions can be obtained from models or by physical testing. For complex structures, such as a helicopter transmission, the modeling approach becomes very complex and difficult to apply. Therefore, testing is typically performed to obtain accurate transfer functions. In the traditional testing technique, a sinusoidal force is applied at one position on a structure and the response (usually acceleration) is measured at a second point on the structure. By sweeping the sinusoidal force through a range of frequencies and plotting amplitude ratio and phase angle, an experimental transfer function is obtained.[12]

In structures where it is difficult to obtain the overall transfer function (because of shaker or transducer placement difficulties), it may be possible to test individual components individually and then, using mechanical impedance techniques, combine the individual responses to give the overall response.[13] This has been successfully done for a truck frame and body. It is likely that much further development of this technique would be necessary in order to apply it to a helicopter transmission.

The use of transient pulse excitation has, due to the availability of improved computational facilities, become an increasingly popular method of obtaining mechanical transfer functions.[14] In applying this technique, the system is forced with a sharp pulse at the forcing point and the response is measured at some other point. The transfer function between the response and force can be obtained from the spectral density calculations involving the input force and output motion. Estimates of system linearity and transfer function accuracy can be made by observing the coherence function between the two signals.

Finally, another common technique for finding system resonances, but not transfer functions, is to start up or shut down a piece of rotating machinery. Here, the speed of the machine is either increased or slowed down at a fairly constant rate. The vibration amplitude is plotted as a function of speed. Amplitude peaks on this plot indicate speeds where resonances exist. These resonances are often excited at the shaft rotating frequency and are often related to the critical lateral frequencies of the shafting system.

Transfer Functions in Geared Systems

In analyzing geared systems, two types of excitation might be considered:

1. Force excitations at the gear mesh
2. Force excitation due to faulty bearings

Gear Mesh Excitation

Gear mesh forces are transmitted from the tooth mesh to the housing through the shafting and bearings via both lateral and torsional vibrations of the shafting system. These vibrations, in turn, excite the bearing, which then excites the housing upon which the vibration transducer is typically mounted. This problem has been studied by

Wang,[15] Laskin, et al.,[16] Badgley and Laskin,[17] and Badgley and Chiang.[18]

The experimental transfer function analysis between the gear mesh and transducer location, in the opinion of the authors, has never been accurately applied on a helicopter gear transmission due to some physical problems in locating the vibration exciter at the gear mesh. However, these problems may be circumvented by placing the exciter at the transducer location and measuring the resulting forces at the gear mesh. Perhaps the most promising means of measuring the mesh transducer transfer function is with impulse testing, where a force pulse is applied at the gear mesh and, through appropriate data reduction, the transfer function is obtained. This technique assumes system linearity, which must be ascertained before pulse testing results can be relied on.

Bearing Dynamics

Transducers may be located very close to bearings on the periphery of gearboxes, thus eliminating some of the transfer dynamics problems which may occur in gearing. However, some of the helicopter main transmission bearings are located in central portions of the gearbox, where transducers are difficult to locate or must be built into the unit. When external transducers are used in an attempt to detect faults from these inner bearings, the transfer function between the bearing and transducer again plays an important role. Resonances will amplify vibrations and antiresonances will attenuate vibrations in certain frequency ranges. If test speeds should change, serious errors may result in the data analysis.

Bearing transfer functions can be determined theoretically, but again actual physical testing is the best way to obtain accurate transfer functions.

Where the number of transducers to be placed on a given transmission is a limiting factor, the transfer dynamics between the transducer and the several bearings it is monitoring become even more important. In this instance, the use of transfer function analysis would be a systematic way of selecting optimum transducer locations for the monitoring of several bearings.

MATHEMATICAL TECHNIQUES

A typical vibration diagnostic system is of the form shown in the block diagram of Figure 8. Normally, a vibration transducer is placed on the vibrating structure at a position on or near the part which is being monitored. In recent years the piezoelectric accelerometer has been the most popular transducer, but this has not ruled out the use of noncontacting displacement transducers or velocity pickups for motion measurement. The vibration transducer produces a time-varying signal which is fed into a processor which performs some form of mathematical analysis on the time function. There are many forms of signal analysis which this processor may perform, but they can essentially be broken into either time domain techniques or frequency domain techniques. Also, purely statistical techniques could be treated as a separate class. However, in this report, they will be included in the discussion of time and frequency domain techniques. Specific characteristics of the new mathematical function which results from the processor are then identified and used to classify the system's condition. These characteristics are identified as discriminants and are the number or set of numbers which is used to identify a part's condition. These discriminants either are obtained from prior knowledge of the mechanical behavior of the system or are determined by purely statistical techniques, which will be called pattern recognition discriminants hereafter. The discriminants are then compared in some manner with past data or with some mechanical basis to decide the condition of a component or system.

In this section, time and frequency domain processing of time series data will be discussed, with primary emphasis placed on the means of mathematically analyzing transducer signals. A short section on digital processing techniques will be included since this form of processing is becoming more prevalent in the signal analysis field. Different techniques for obtaining discriminants and the methods of applying discriminants are discussed later.

Many books and publications have been written on these topics. Among them are books by Bendat and Piersol,[19] Jenkins and Watts[20] and Enochson and Otnes.[21] Information contained in these books will be summarized. This summary will not become involved with the complex mathematical and statistical details which are necessary for a complete understanding of the various techniques.

TIME DOMAIN TECHNIQUES

In this report, time domain technique will refer to all techniques which perform simple computations directly on the time signal and those mathematical techniques which give a parameter output in which time is the independent variable. Techniques which fall into this category and which will be discussed are:

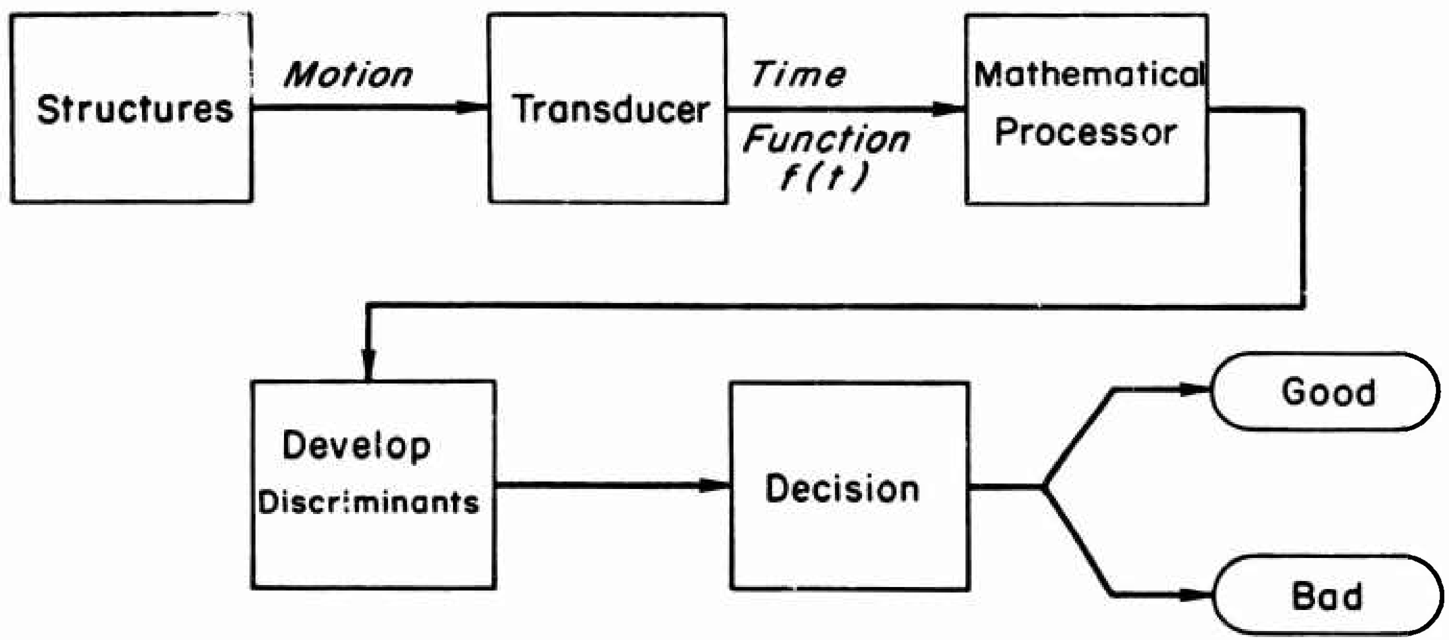


Figure 8. Basic Diagnostic System.

1. Mean square values.
2. Probability density functions and other statistical representations.
3. Correlation functions.
4. Time averaging.
5. Band-pass filtering prior to items 1-4.

Mean-Square Values

Perhaps the simplest means of analyzing time series data is to obtain the average amplitude or general intensity of the data. This is normally done with the mean-square value, ψ_x^2, which, for a time history x(t) may be expressed in equation form.

$$\psi_x^2 = \lim_{T \to \infty} \frac{1}{T} \int_0^T [x(t)]^2 \, dt \tag{21}$$

The positive square root of the mean-square value is the root-mean-square (RMS) value.

The average or mean value μ_x of x(t) may be represented by

$$\mu_x = \lim_{T \to \infty} \frac{1}{T} \int_0^T x(t) \, dt \tag{22}$$

The dynamic component of x(t) may be described by a variance, σ_x, which is the mean-square value about the mean:

$$\sigma_x^2 = \lim_{T \to \infty} \frac{1}{T} \int_0^T [x(t) - \mu_x]^2 \, dt \tag{23}$$

By expanding the above relation

$$\sigma_x^2 = \psi_x^2 - \mu_x^2 \tag{24}$$

In computing the above relations, one must have stationary data of sufficient length to allow little fluctuation in the computed quantities. If the length of computation T is shortened sufficiently, the mean square value will fluctuate even though the data is stationary.

In vibration data taken from accelerometers or velocity pickups, the data should always have a mean value $\mu_x = 0$ since most machinery is relatively stationary and will not have static velocities or accelerations. Even moving bodies, such as helicopters, can be treated in this manner since the static velocities and accelerations are small relative to the vibration levels of individual components.

Mean-square values have had some utility in diagnostics, particularly where the vibration signal is a single frequency which predominates over all others. This is typical of displacement measurements for which the shaft rotational frequency is predominant. Displacement amplitude is often used as an indicator of shaft unbalance. Root-mean-square values can sometimes be used to sense overall changes in the signal, but only if the changes are gross or at the primary frequency components.

Probability Density Function and Other Statistical Representations

The probability density function is a means of statistically representing data in an amplitude histogram format. It expresses the probability that the data will be at a value within a given range at any instant in time. The equation describing the probability density function can be developed with the aid of Figure 9.[22]

In Figure 9, the probability that x falls into the range between x and $x + \Delta x$ is $\dfrac{\sum_{i=1}^{k} \Delta t_i}{T}$. If we let $T \to \infty$, we can define the probability as

$$\Pr\left(x < x_{(t)} < x + \Delta x\right) = \lim_{T \to \infty} \frac{\sum_{i=1}^{\infty} \Delta t_i}{T} \tag{25}$$

The probability density function can now be defined by letting $\Delta x \to 0$.

$$p(x) = \lim_{\Delta x \to 0} \frac{\Pr(x \leq x(t) < x + \Delta x)}{\Delta x} = \lim_{\Delta x \to 0} \lim_{T \to \infty} \frac{\sum_{i=1}^{k} \Delta t_i}{T\Delta x} \tag{26}$$

The probability density function is plotted as a continuous-amplitude histogram as shown in Figure 10 for examples of wide-band random noise and a pure sinusoidal signal.

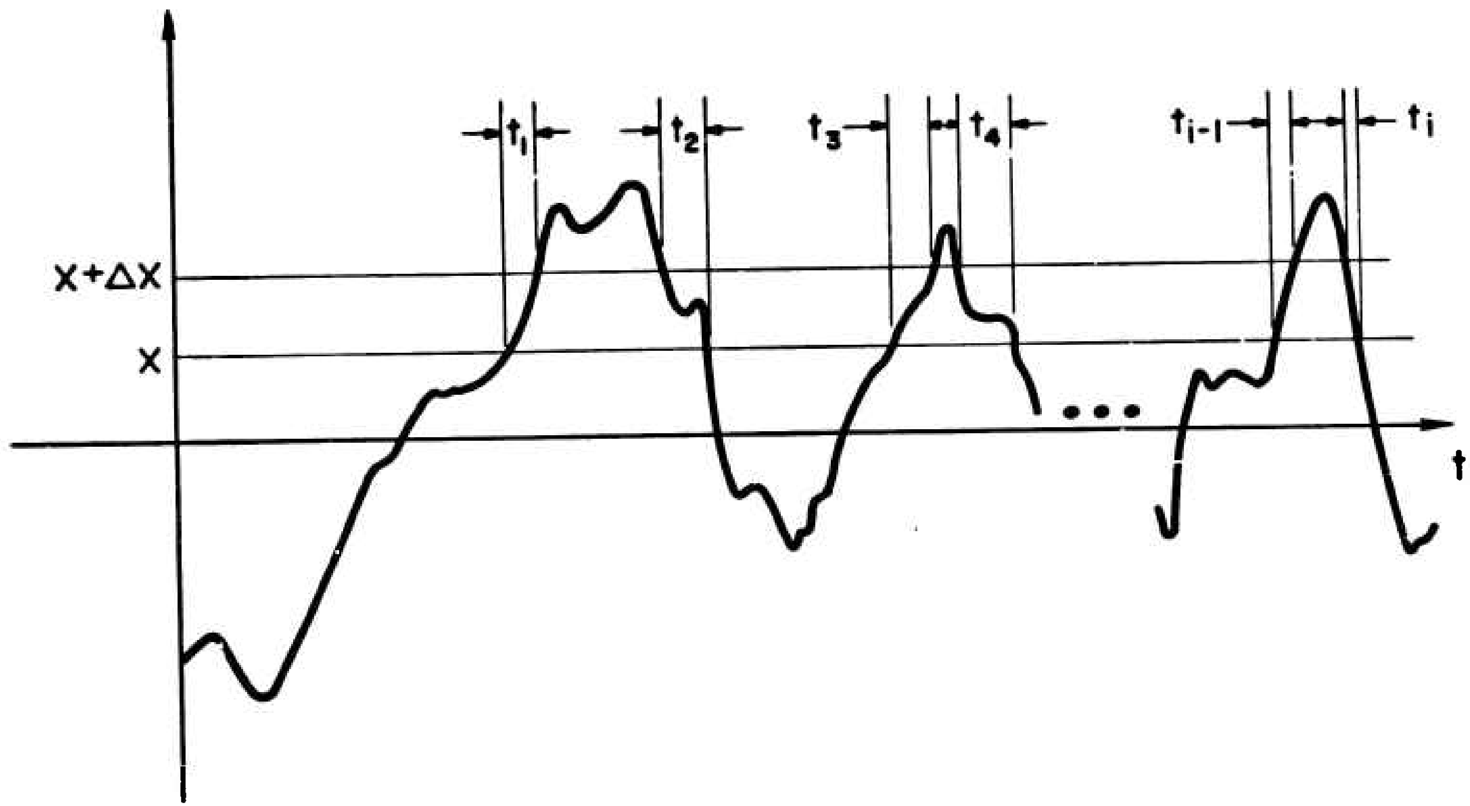


Figure 9. Measurement of Probability Density.

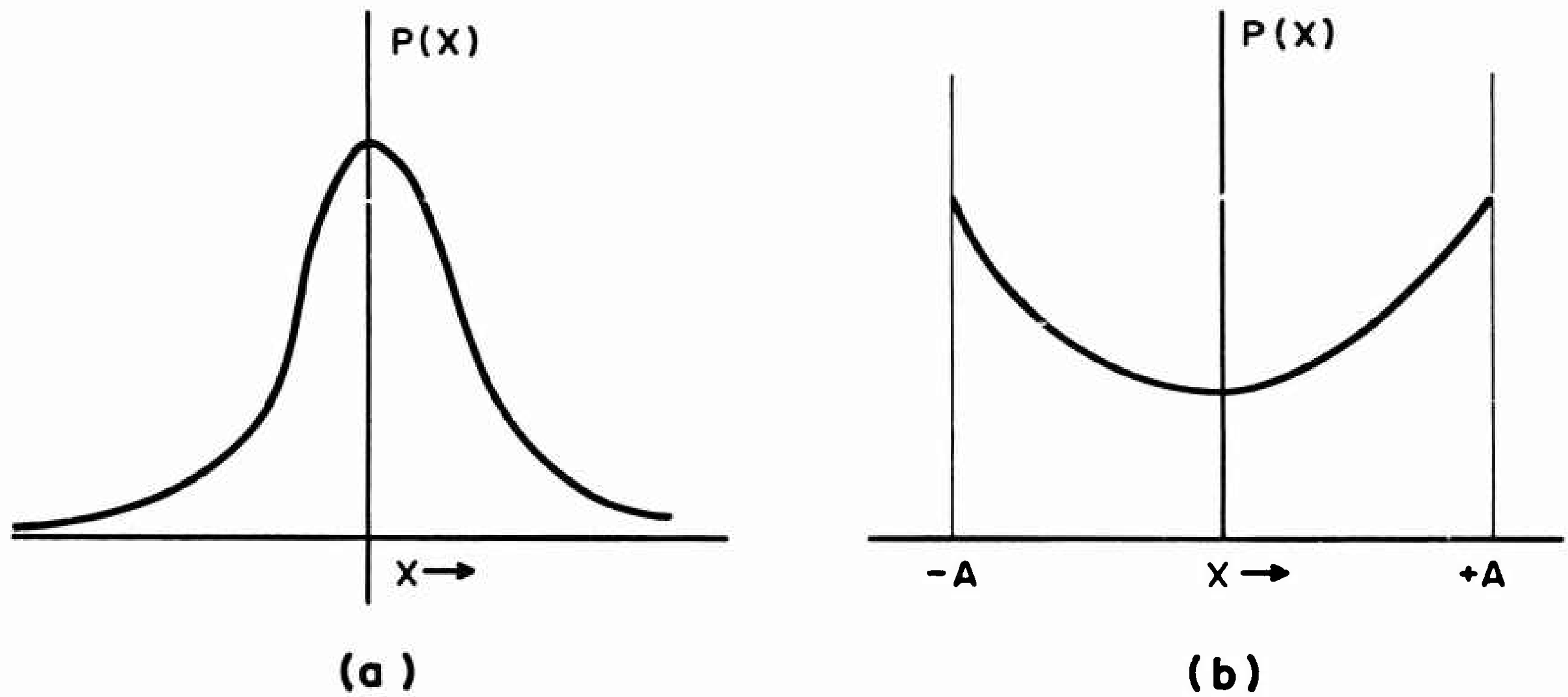


Figure 10. Probability Density Functions.
a. Wide-Band Random Noise
b. Pure Sinusoid

Another useful statistical representation of data is the cumulative probability distribution which is the probability that x(t) is less than or equal to some value of x and is defined by

$$P(x) = Pr[x(t) \leq x] = \int_{-\infty}^{x} p(x)\, dx \tag{27}$$

Useful relations may be obtained from the probability density function such as the mean value μ_x:

$$\mu_x = \int_{-\infty}^{\infty} x\, p(x)\, dx \tag{28}$$

and the mean-squared value:

$$\psi^2 = \int_{-\infty}^{\infty} x^2\, p(x)\, dx \tag{29}$$

Other statistical treatments of data which may be useful in diagnostic systems include number of zero crossings or data crossings at any amplitude level, distribution of peak (zero slope) values of x(t), and other types of ratios, sums, and differences of data statistics.

All of the probability density techniques have been implemented with analog and digital instruments. The digital processors are particularly simple since they require only level detectors and additive memories for each amplitude level. Analog techniques have been implemented on several commercial analyzers. In performing probability density analysis, care must be taken to use long enough data samples that average and not instantaneous statistical data is obtained.

Correlation Functions

Both the autocorrelation function and the cross-correlation function deal with the time representation of signals. The autocorrelation function of a time signal x(t) is a graph of the similarity between the waveform x(t) and a replica of itself $x(t + \tau)$ displaced by a length of time τ from x(t). The autocorrelation function is defined by the equation

$$R_x(\tau) = \lim_{T \to \infty} \frac{1}{T} \int_{0}^{T} x(t)\, x(t + \tau)\, dt \tag{30}$$

where $R_x(\tau)$ = autocorrelation.

Typical autocorrelation functions for a sinusoidal wave, wide-band random noise, and wide-band random noise added to a sine wave are shown in Figure 11.

For the autocorrelation function, the mean value of $x(t)$ may be found from $\mu_x = \sqrt{R_x(\infty)}$. The mean-square value may be found from $\psi_x^2 = R_x(0)$. The value of the autocorrelation function will be a maximum at $\tau = 0$. Also, the function is dependent upon the frequency content of the waveform rather than on the actual waveform itself.

The autocorrelation function has received wide use in extracting periodic data from extremely noisy signals. This would appear to make it a prime candidate as a diagnostic analysis technique since much of the usable diagnostic information may be deeply buried in noise. Further discussion of the autocorrelation function as a diagnostic tool is given later in the report.

A similar function to the autocorrelation function is the cross-correlation function $R_{xy}(\tau)$. The cross-correlation function compares two different signals in a manner similar to the autocorrelation function and is defined by the expression,

$$R_{xy}(\tau) = \lim_{T \to \infty} \frac{1}{T} \int_0^T x(t)\, y(t + \tau)\, dt \qquad (31)$$

The cross-correlation function is not necessarily a maximum at $\tau = 0$ and is not an even function as is the case with the autocorrelation function.

The cross-correlation function is a valuable tool for measurement of time delays in a system and also for determination of transmission paths of signals. The recovery of a signal which is buried in noise is also possible with the cross-correlation function, but only when the desired signal one wishes to detect is known. In this specific case, a greater output signal-to-noise ratio will be obtained than with the autocorrelation function.

There are several instruments on the market which are specifically designed to perform correlation function analysis on raw data. Both analog and digital processing is used in these instruments. Between 100 and 400 time lags are available on typical analog correlation analyzers. A more powerful and more flexible means of performing correlation function analysis is with digital computation, where much higher resolution and accuracy can be obtained.

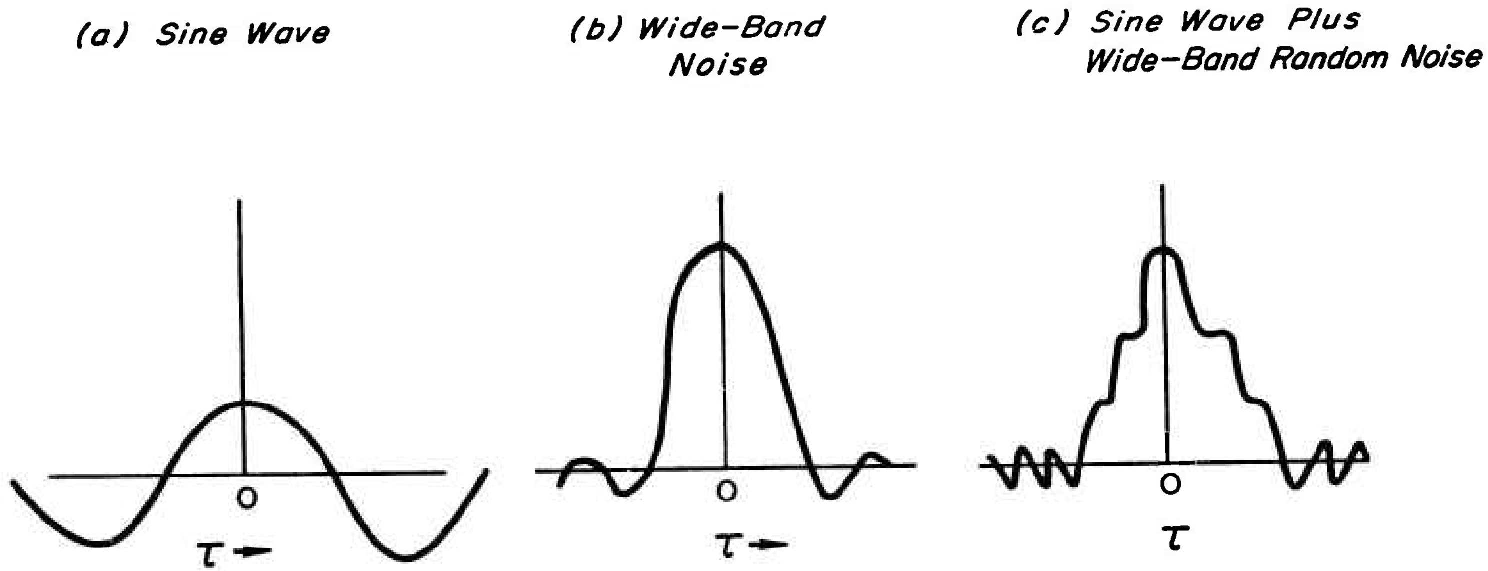


Figure 11. Correlation Functions of Various Signals.

Time Averaging

Time averaging, which is also called time summation, coherent averaging, signal enhancement, and ensemble averaging, is another mathematical means of improving the signal-to-noise ratio of a periodic signal that is buried in noise. Many instruments are available for time averaging, but most diagnostic applications of this technique have been developed by General Electric Company.[23]

In time averaging, time blocks of the input function are added to one another in such a manner that signals, which are periodic to the block length or its multiples, will add to one another. Random data and signals with other periodicity will cancel out. This is shown schematically in Figure 12.

In following this procedure, the time signal is partitioned into N segments of length T_s. Each of the N periods of length is coherently added. In this manner signals with period T_s will prevail since they will be additive in each segment of time. The procedure is expressed mathematically as

$$F(\tau) = \sum_{n=1}^{N} f[\tau + (n - 1)T_s] \qquad 0 \leq \tau \leq T \tag{32}$$

where T_s, T and N are defined in Figure 12. An example of the power of this technique is evidenced where an incoming signal with signal-to-noise ratio of -30 dB is averaged over 10^5 summations. The resulting averaged response will have a +20 dB signal-to-noise ratio.[24]

Although this technique outwardly appears to be very simple to apply, particularly with digital processing techniques, some difficulties may be experienced in obtaining an accurate pulsing signal with period T_s to trigger the process. This is primarily caused in rotating machinery by slight speed variations, which can cause difficulties in the phasing of higher harmonics of frequencies with period T_s. An example of this problem is shown in Figure 13. The figure could depict the response of a system to repeated bearing impacts resulting from a spall on a bearing race. If time averaging is applied to the system of Figure 13, an error of 0.00005 sec in T_s would cause the 10,000-Hz rings to cancel rather than add as is desired. This obviously would cause gross errors in the resulting analysis. An error of 0.00005 sec could be caused by a slight variation in the shaft speed or slight skidding in the bearing.

One of the techniques which has been developed to counteract this problem is to use a tachometer signal from the shaft to trigger the summation process. The tachometer signal may be processed through a tracking ratio synthesizer to generate a trigger signal which is proportional to the shaft speed and, thus, T_s adjusts accordingly. This process has helped

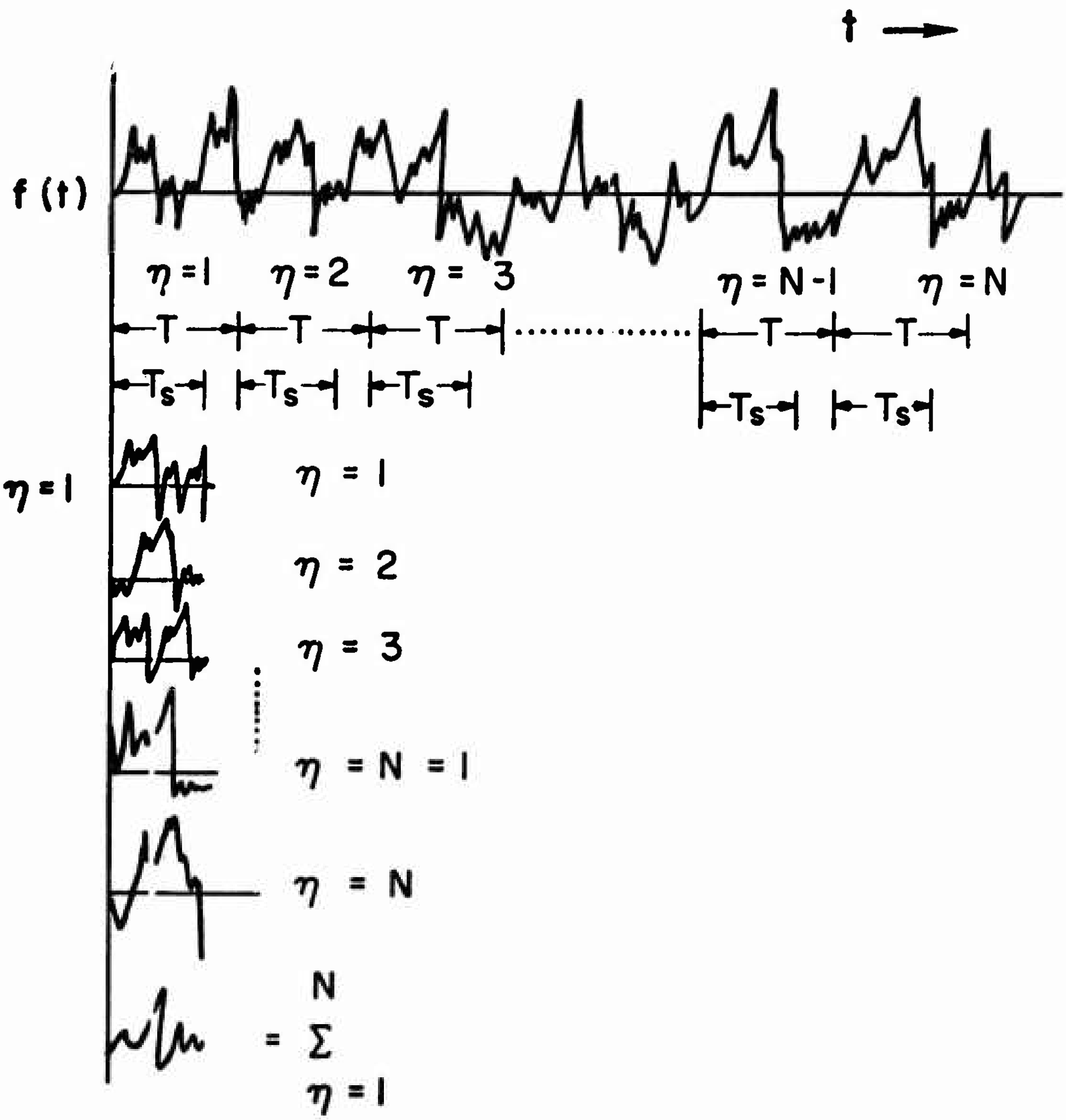


Figure 12. Schematic of Time-Averaging Procedures.

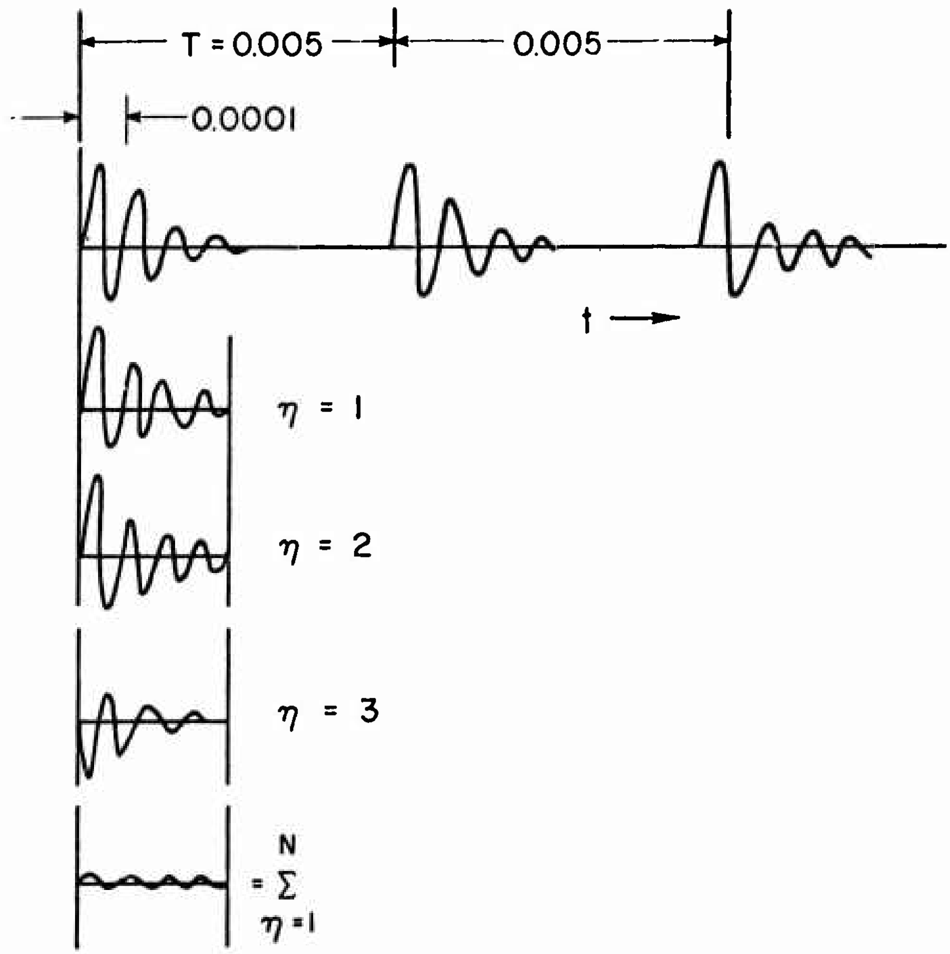


Figure 13. Errors in Time Averaging Due to Incorrect Synchronization.

compensate for speed fluctuations. A further aid has been to first rectify the signal prior to averaging; this eliminates the problem of cancellation of the high-frequency components, but it reduces the signal-to-noise improvement since the random noise will never totally cancel as it will with an unrectified signal.

Band-Pass Filtering

Often the information from a function of time may be heavily affected by signals at a particular frequency or range of frequencies. A typical example is the vibration at the upper mast bearing on a helicopter's main transmission. The vibration signal measured at this point shows a strong component at the rotor blade pass frequency which, when performing any of the above-mentioned time domain techniques, can greatly alter the analysis. In particular, this rotor frequency is so low that it makes the analysis appear nonstationary in some procedures for computing probability density, correlation, or time-average functions. By filtering out this low-frequency component, it is possible to obtain a more reasonable analysis.

Also, high-frequency components can have a similar effect and may require low-pass filtering. Frequencies within the analysis range may also be adjusted or filtered by pre-whitening or other signal conditioning techniques.

FREQUENCY DOMAIN TECHNIQUES

Analysis of time-series data may be performed in the frequency as well as time domain. The frequency domain is categorized by reference to cycles (or events) per unit time rather than time itself. In the most general terminology, this variable is sometimes called sequency, which is defined as zero crossings per unit time.

There are several frequency domain analysis procedures which will be discussed. Basic to all of these is the frequency-amplitude or frequency spectrum calculation. Using this computation, several specialized functions such as coherence, cepstrum(defined on page 46), spectral correlation, etc., may be obtained.

Two basic terms that appear in frequency domain analysis need to be defined initially--hertz (Hz) is cycles per second, and decibels (dB) is 20 $\log_{10} A_s/A_{ref}$, where A_s is the amplitude of signal measured and A_{ref} is amplitude of reference signal. Often, the reference signal amplitude is unity, which is used to nondimensionalize the argument of the logarithm.

Power Spectral Density (PSD)

The power spectral density is the most generally used measure in frequency domain analysis. It is an indication of the energy of a signal which may be associated with a given frequency. It may be defined in either of two

ways: by the Fourier transform or by the autocorrelation function of a signal. Autocorrelation has been previously defined, but some discussion of the Fourier transform is required before continuing with the discussion on power spectral density.

Fourier transform analysis is a decomposition of a time domain signal into the frequency domain. Its simplest form is the Fourier series. If a signal $x(t)$ is purely periodic of period T, it may be written as a series in the form

$$x(t) = a_o + \sum_{n=1}^{\infty}\left(a_n \cos\frac{2\pi nt}{T} + b_n \sin\frac{2\pi nt}{T}\right) \tag{33}$$

where

$$a_n = \frac{2}{T}\int_0^T x(t) \cos\frac{2\pi nt}{T}\, dt \qquad n = 0,1,2,3\ldots \tag{34}$$

$$b_n = \frac{2}{T}\int_0^T x(t) \sin\frac{2\pi nt}{T}\, dt \qquad n = 1,2,3,4\ldots \tag{35}$$

In cases where the signal is not known to be purely periodic, the more general Fourier transform is used. It may be written as follows:

$$x(f) = \lim_{T\to\infty}\int_{-T}^{T} x(t) \exp[-j2\pi ft]\, dt \tag{36}$$

where f = frequency of interest. This function is continuous rather than discrete. The Fourier transform may have a real and an imaginary part and is often represented in amplitude-phase angle form.

$$\begin{aligned} x(f) &= Re(f) + j\, Im(f) \\ &= A(f)\angle\varphi(f) \end{aligned} \tag{37}$$

where $A = \sqrt{Re^2 + Im^2}$, function of frequency
$\varphi = \tan^{-1}[Im/Re]$, function of frequency.

Power spectral density may be defined in terms of the Fourier transform by the following equation:

$$S(f) = \int_{-\infty}^{\infty} E[X^*(f)\ X(g)]\ \exp[j2\pi(g-f)t]\ dg \tag{38}$$

where $E[X^*(f)\ X(g)]$ = expectation of the Fourier transform times its conjugate. It may also be defined in terms of the previously discussed correlation function $[R_x(\tau)]$ by

$$S\ (f) = \int_{-\infty}^{\infty} R\ (\tau)\ \exp[-j2\pi f\tau]\ d\tau \tag{39}$$

The PSD may be calculated either by the use of analog filtering or by a direct digital computation of one of the transformations. Two types of analog filtering systems that are used to calculate the PSD are (1) banks of parallel band-pass filters and (2) swept frequency analyzers that utilize a single band-pass filter which is swept through the frequency range or the similar effect achieved through heterodyning. The digital mechanizations will be discussed later.

Frequency response of a typical band-pass filter may be seen in Figure 14. As can be seen, the filter will allow a range of frequency components (or portion of the spectrum) to pass while attenuating the other frequencies. In discussing the filter characteristics, we usually speak of three main parameters: bandwidth, center frequency, and roll-off. Bandwidth can be defined as the half-power interval, i.e.. range of frequencies for which filter response will be within 3 dB of the peak. Center frequency is that frequency which is in the middle of the bandwidth. Roll-off refers to the attenuation rate of the signal. It is generally dimensioned in decibels per decade, where a decade is a power of ten change in frequency.

By passing a time domain signal through a filter, an approximate value of Fourier amplitude at that frequency will be obtained. The value is approximate since it is obtained for a range of frequencies, i.e., over a finite bandwidth, and the input sample is of finite length rather than the infinitely long value as used in the definitions. With the output of the filter defined as $x(t,f_c,BW)$, the PSD approximation may be written as

$$S_x(f_c) = \frac{1}{(BW)T} \int_0^T x^2(t,f_c,BW)\ dt \cong \frac{|x(t,f_c,BW)|^2}{BW} \tag{40}$$

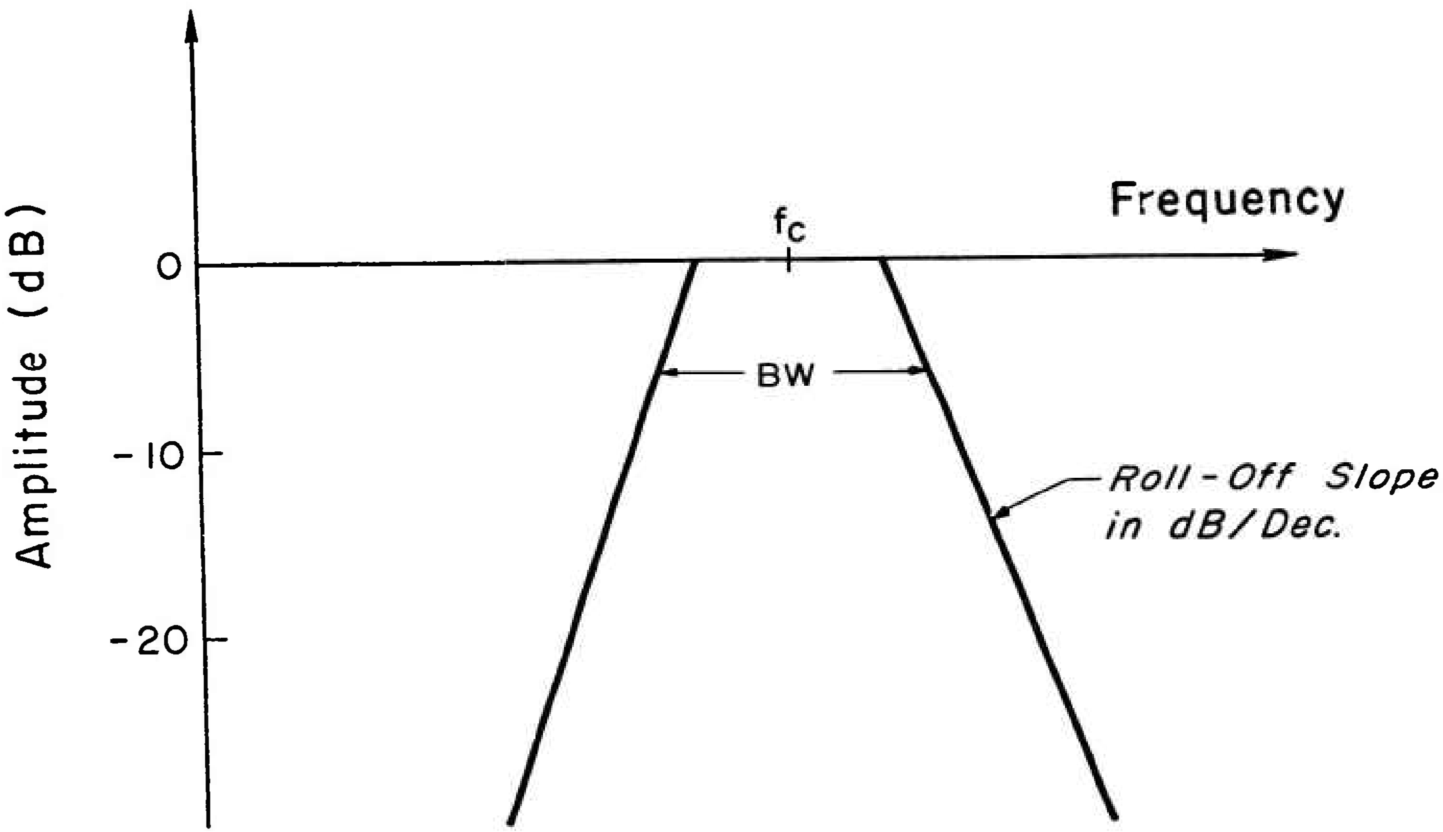


Figure 14. Characteristic Filter Response.

where f_c = center frequency of filter and T = length of data sample. The squaring, integration, and division are easily performed by analog circuitry. A block diagram of the procedure is shown in Figure 15.

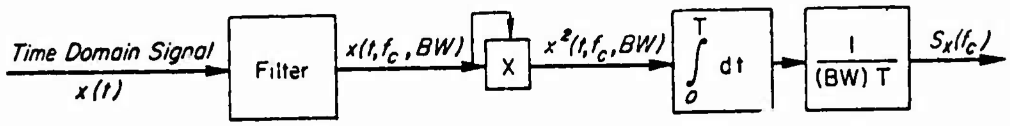


Figure 15. Block Diagram of Calculation of PSD via an Analog Filter.

There are some constraints on any analysis which utilizes this filtering procedure. It has been found, through experience, that the bandwidth of the filter must be less than or equal to one-fourth the desired analysis bandwidth. Thus, if an analysis bandwidth of 20 Hz is desired, a filter with a bandwidth of 5 Hz or less is required. Since a broad bandwidth filter and a finite integration time is used, a static error is introduced. This error can be expressed in terms of the standard deviation of the measured power density function.

$$T[S_x(f)] = \frac{S_x(f)}{\sqrt{(BW)T}} \tag{41}$$

where $T[S_x(f)]$ = the standard deviation of the measured power spectrum. A ratio is usually defined.

$$\frac{T[S_x(f)]}{S_x(f)} = \frac{1}{\sqrt{(BW)T}} \tag{42}$$

Thus,

$$\epsilon \approx \frac{1}{\sqrt{(BW)T}} \tag{43}$$

This means that for a given measurement of the power spectral density, the error between the measured power density and the true power density will be $\pm\ \epsilon$ with a confidence level of 67%; i.e., two-thirds of the measurement will be within $\pm\ \epsilon$. This formula is an approximation which holds for $\epsilon < 0.2$. If the error becomes greater than 0.2, the deviation takes on a chi-squared distribution and must be found from it.

To utilize the chi-squared tables, a parameter called the degrees of freedom (n) of the analysis must be found.

$$n = 2(BW)T \tag{44}$$

Going to a chi-squared table or chart, which is available in almost any statistics book, the value of the ratio of the true mean square to the observed mean square may be found for a variety of confidence levels.[25]

These considerations are all that are essential to the operation of the most simple PSD analyzers, i.e., those analyzers which do not use swept frequency analysis. These devices will give a discrete PSD, i.e., a set of PSD values at individual frequencies. Often, lines are drawn between the points to give an extrapolation to a continuous PSD.

A PSD plot can also be produced using a single filter. In this type of machine, the filter is "swept" through the frequency range of interest either by actually changing the center frequency or heterodyning on the signal. The output of the filter is the Fourier component, which may be manipulated to give PSD. However, the time required to produce the analysis is greatly increased. The filter must not sweep at a rate faster than that at which the filter can respond. The filter has a finite rise time based on its dynamic characteristics, which is approximated by

$$T_r = \frac{2\pi}{BW}, \qquad \text{sec} \tag{45}$$

For true averaging, the sweep rate is

$$S.R. \leq \frac{BW}{T_r}, \qquad \text{Hz/sec} \tag{46}$$

The time required to produce a spectrum depends on this sweep rate and the frequency range of interest. If the frequency range is F Hz wide, analysis time required (T_a) is

$$T_a = \frac{F}{SR} \tag{47}$$

This value is a function of filter characteristics and allowable error as well as the frequency range of interest.[26] Also, if a long sample of data is not available, the data may be put into a tape recorder loop.

To overcome the difficulties which may arise from such a long analysis time, time-compression devices (so-called real-time analyzers) have been developed. The input data is digitally sampled and then speeded up. This speedup causes a frequency translation. For example, speeding up by a factor of 100 would translate a 1-kHz bandwidth signal to one of 100 kHz. As the signal bandwidth is increased, the filter bandwidth can also be increased and still give the same effective resolution. Since processing time is inversely related to bandwidth, the time required for the analysis is greatly reduced.

Figure 16 shows a block diagram of a time-compression device. The input signal is sampled via an A/D converter, speeded up, and then fed through a D/A converter. This signal is then analyzed via a heterodyne analog filter. The memory is recycled a given number of times and the heterodyning adjusts the effective filter position for each sweep. The number of recirculations of the data (or, equivalently, the number of center frequencies set for the filter) is the number of "lines" of the real-time analysis. These "lines" are the number of Fourier components found. It should be noted that "real-time" analyzers do not actually operate in "real time" but are much faster than swept-frequency analyzers.[27]

Power spectral densities may also be found by the use of analog correlation function instrumentation. However, in practice, these devices are seldom used.

Cross-Power Spectral Density

The cross-power spectral density is a property which is used in frequency domain analysis. It is related to power spectral density but involves a calculation using two input signals. The definition may be phrased in terms of Fourier spectra or correlation as follows:

$$S_{xy}(f) = 2 \int_{-\infty}^{\infty} R_{xy}(\tau) \exp(-j2\pi f\tau)\, d\tau \tag{48}$$

where $R_{xy}(\tau)$ = cross-correlation of $x(t)$ and $y(t)$

$$S_{yv}(f) = \frac{1}{2\pi} \int_{0}^{\infty} E\{X(f)\ Y(g)\} \exp[-j2\pi(f-g)]\, dg \cong \frac{1}{2\pi} |X^*(f)Y(f)| \tag{49}$$

$X^*(f)$ = conjugate of Fourier component

The calculation is usually performed digitally. The results show an indication of the commonality between two signals in the frequency domain.

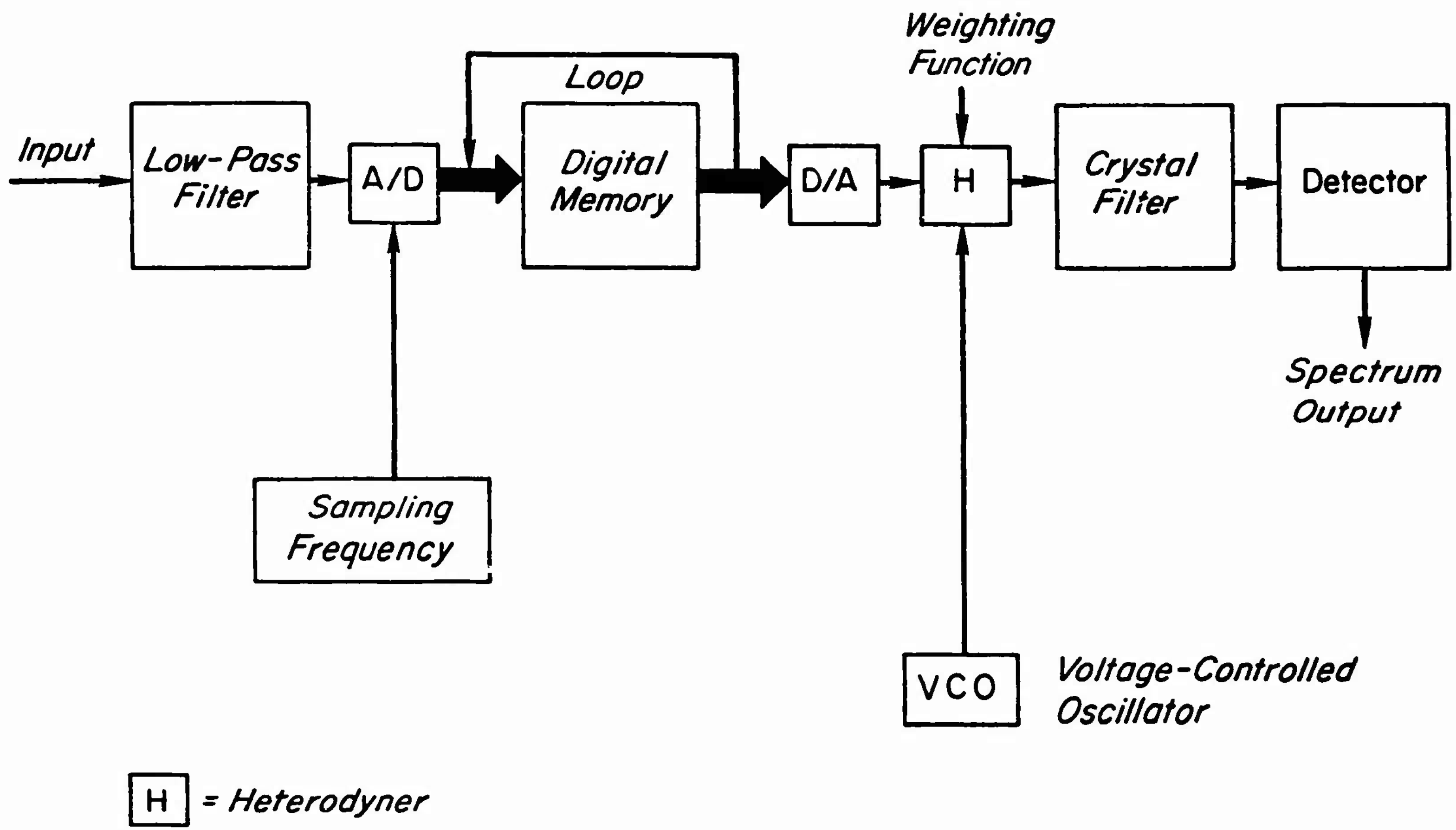


Figure 16. Simplified Block Diagram of Time-Compression Analyzer.

Transfer Functions

Another of the properties calculated via PSD analysis is the transfer function, discussed earlier, of some machine or signal transmission path. With a system as shown in Figure 17, a transfer function may be found in the following forms:

$$TF(f) = \frac{Y(f)}{X(f)} \tag{50}$$

or

$$TF(f) = \frac{S_{xy}(f)}{S_{xx}(f)} \tag{51}$$

The second form is found to be the better estimate in the case of systems with internal noise generation.

These transfer function analyses can be performed via analog analyzers or digital processors.

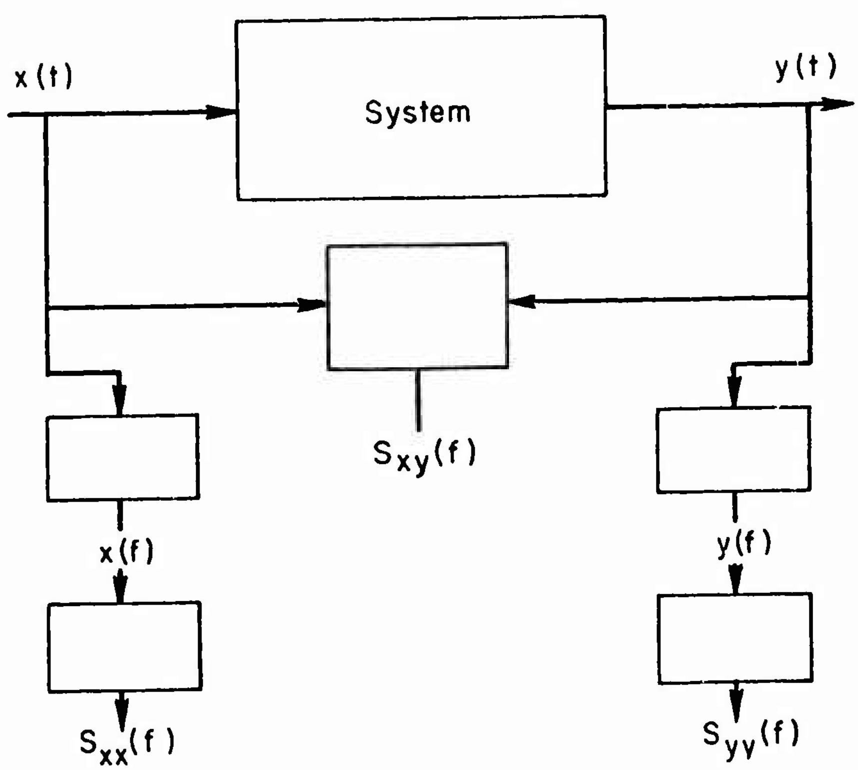


Figure 17. Block Diagram of Transfer Function Analysis.

Coherence Functions

The coherence function (γ^2) is a frequency domain analysis which gives an indication of the interrelationship of two signals. By definition, it is

$$\gamma^2(f) = \frac{|S_{xy}(f)|^2}{S_x(f)\ S_y(f)} \qquad (52)$$

The value of the coherence function always lies between 0 and 1. If a coherence of value 1.0 is achieved, the signals are considered coherent or completely related, i.e., the output is completely determined by the input. As the coherence drops toward zero, this relationship lessens. A coherence of zero would indicate totally unrelated signals.[28]

The coherence function is often used in transfer function analysis to determine the points of maximum validity of a transfer function. At frequencies where high coherence exists, the transfer function amplitudes may be considered usable. Where low coherence exists, the validity of the transfer function is doubtful. The coherence function has also been used to determine the sources of noise components. In the case of an environment with several noise sources, a coherence function can be performed between the signal received with a nondirectional microphone and an accelerometer mounted on the piece of equipment of interest. The noise spectrum can then be weighted by the values of the coherence function.[29]

Cepstrum

The language of this cepstrum analysis is a takeoff on the language of spectrum analysis. An equivalency would show:

Spectrum ⟷ cepstrum
frequency ⟷ quefrency
filtering ⟷ liftering, etc.

A cepstrum is defined as a power spectral density of a power spectral density and is used to pick fundamental periods out of a signal. If a signal contains a strong periodic component other than a pure sine wave, the spectrum will show "spikes" in amplitude at the fundamental frequency and its harmonics (multiples). If a PSD analysis of the spectrum is run, the result will be in the quefrency domain where

$$\text{quefrency} = \frac{\text{cycles}}{\text{cycles/sec}} = \text{sec}$$

The resulting peaks in the cepstrum will show the fundamental periodicity between peaks.

The cepstrum analysis is generally performed digitally.[30]

Spectral Correlation

Spectral correlation is another analysis to determine periodic relationships between spectra. Auto- or cross-correlations may be performed depending upon the desired results. A definition is

$$Q_{xx}(F) = \lim_{T \to \infty} \int_{-T}^{T} X(f + F)\, X(f)\, df \tag{53}$$

$$Q_{xy}(F) = \lim_{T \to \infty} \int_{-T}^{T} X(f + F)\, Y(f)\, df \tag{54}$$

The autocorrelation ($Q_{xx}(F)$) will show peaks at values of frequency delay which could be caused by harmonics or sidebanding. The cross correlation ($Q_{xy}(F)$) will determine if two signals contain the same harmonic content. Here, again, processing is usually digital in nature.

DIGITAL ANALYSIS

While digital analysis is not to be considered a separate analysis domain from the time or frequency domain, certain special considerations are required. Of special interest is an analysis of sampling requirements of digital systems as well as the limitations imposed by sampling.

There are some procedures and analyses which are unique to digital systems. A discussion of the use of Fast Fourier Transform (FFT) Analysis is given as well as a brief discussion of both Walsh Functions and Comb Filtering. Functions, such as the probability density function and correlation functions, may also be computed digitally. However, since there is nothing particularly unique about their digital computation, no special discussion will be included.

Sampled Data Analysis

Any system which utilizes digital components must include some sampling process involving an A/D converter. In such processes, the input data is sampled periodically at the sampling interval and these digital values are the inputs to the analysis procedure. In utilizing any sort of sampled-data analysis, several considerations must be made.

The first of these considerations is that the input signal must have a finite frequency limit; if it does not, a low-pass filter must be used to limit the frequency content. Such filters are called "anti-aliasing" filters. Their need becomes apparent as seen from a sampled sine wave shown in Figure 18. If the sample rate $1/T_s$ is used, the two sine waves of obviously different frequency will be indistinguishable. To avoid this problem, sampling must be done at least at the Nyquist frequency, where the Nyquist frequency is defined as twice the highest frequency contained in the signal. In general practice, a sampling rate somewhat higher than the Nyquist frequency is used (normally 2.5-5 times higher).

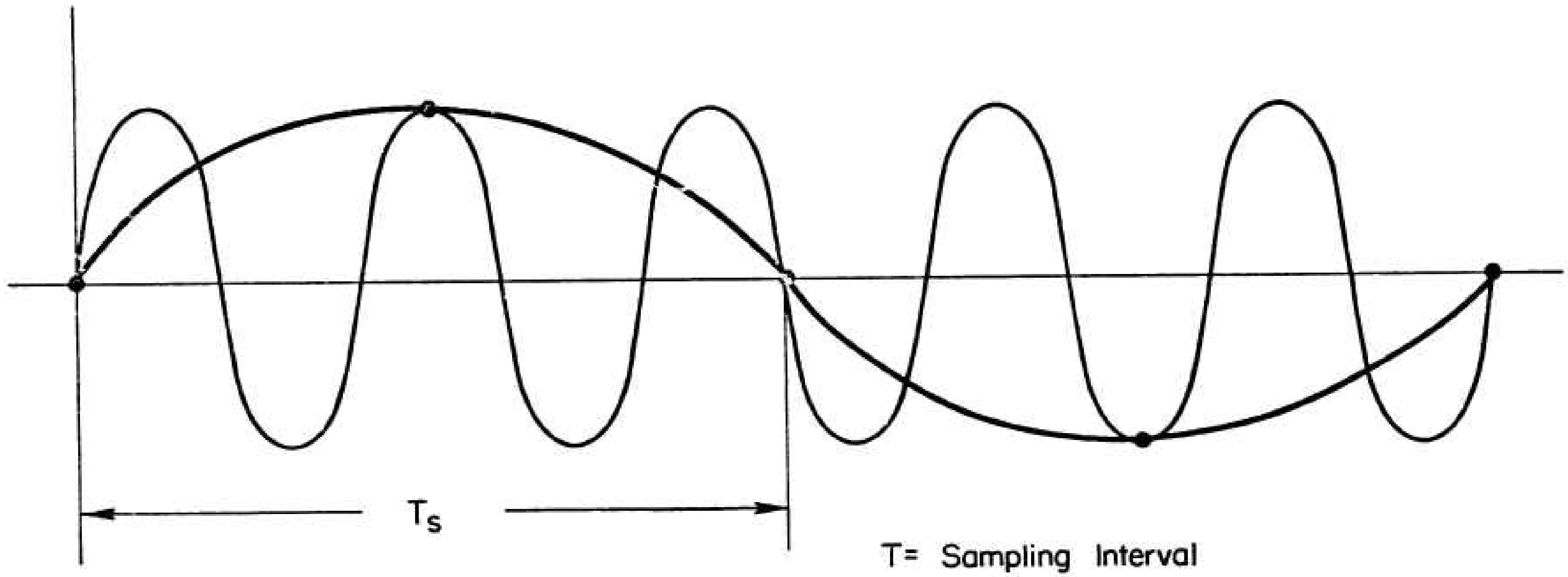


Figure 18. Sampled Sine Waves.

This rate is used because of the finite roll-off characteristics of the anti-aliasing filter which allows a frequency somewhat higher than the filter breakpoint to pass, even though these components are attenuated. This characteristic may be seen in Figure 19.

Another problem involved with sampled-data analysis is leakage, whereby energy contained at a given frequency appears to "leak" to surrounding frequencies. The process of sampling over a finite interval of time causes the data to be effectively multiplied by the "boxcar" function. This function produces a convolution in the frequency domain and thus, the leakage. Figure 20 graphically illustrates this effect. The technique used to overcome the leakage difficulties is to weight the time signal in some manner other than the "boxcar" weighting. Figure 21 shows a typical response with a "Hanning" weighting. The amount of energy which "leaks" to side lobes is diminished, but the effective bandwidth increases.[31] Some typical weighting sequences[32] are shown in Figure 22.

There are other special considerations which must be made when sampling of data is part of an analysis procedure, but aliasing and leakage are the two most important by far.

Fast Fourier Transform

Most of the frequency domain analyses proceed from the calculation of a Fourier transform. In a digital transform, spectral amplitudes are calculated for a finite number of frequency points (sometimes called bins) rather than continuously. If a Fourier transform is written digitally, it takes the form

$$X(f,T) = \Delta t \sum_{n=0}^{n-1} x_n \exp(-j2\pi n f \Delta t)$$

$$= \Delta t \sum_{n=0}^{n-1} x_n \{\cos(2\pi n f \Delta t) + j \cdot \sin(2\pi n f \Delta t)\} \qquad (55)$$

where T = length of data sample
Δt = sampling interval
X_n = nth data point
N = number of data points

To perform the calculations using the standard discrete Fourier transform, the following steps are required:

1. Calculate $\theta_n = 2\pi n f \Delta t$ for all N data points

2. Calculate $\cos \theta_n$ and $\sin \theta_n$

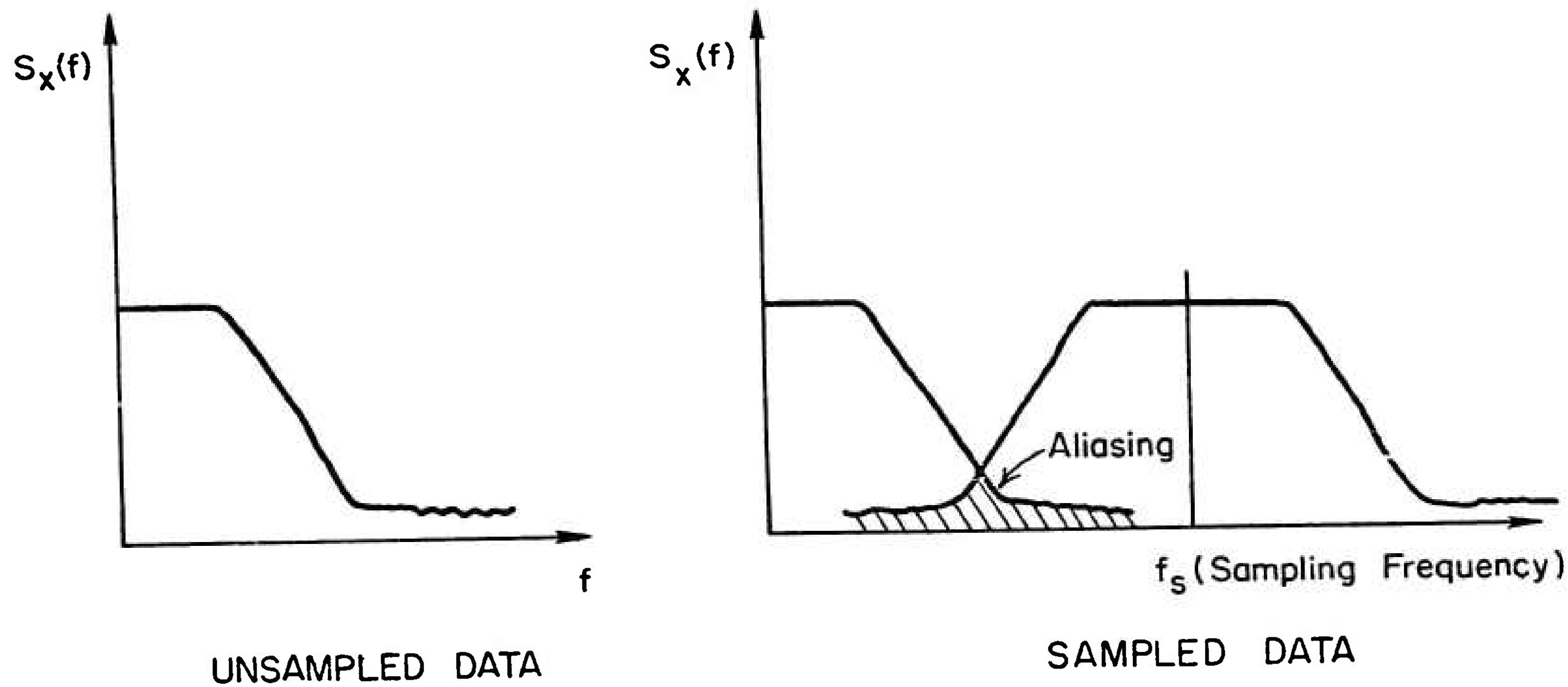


Figure 19. Aliasing Due to Filter Characteristics.

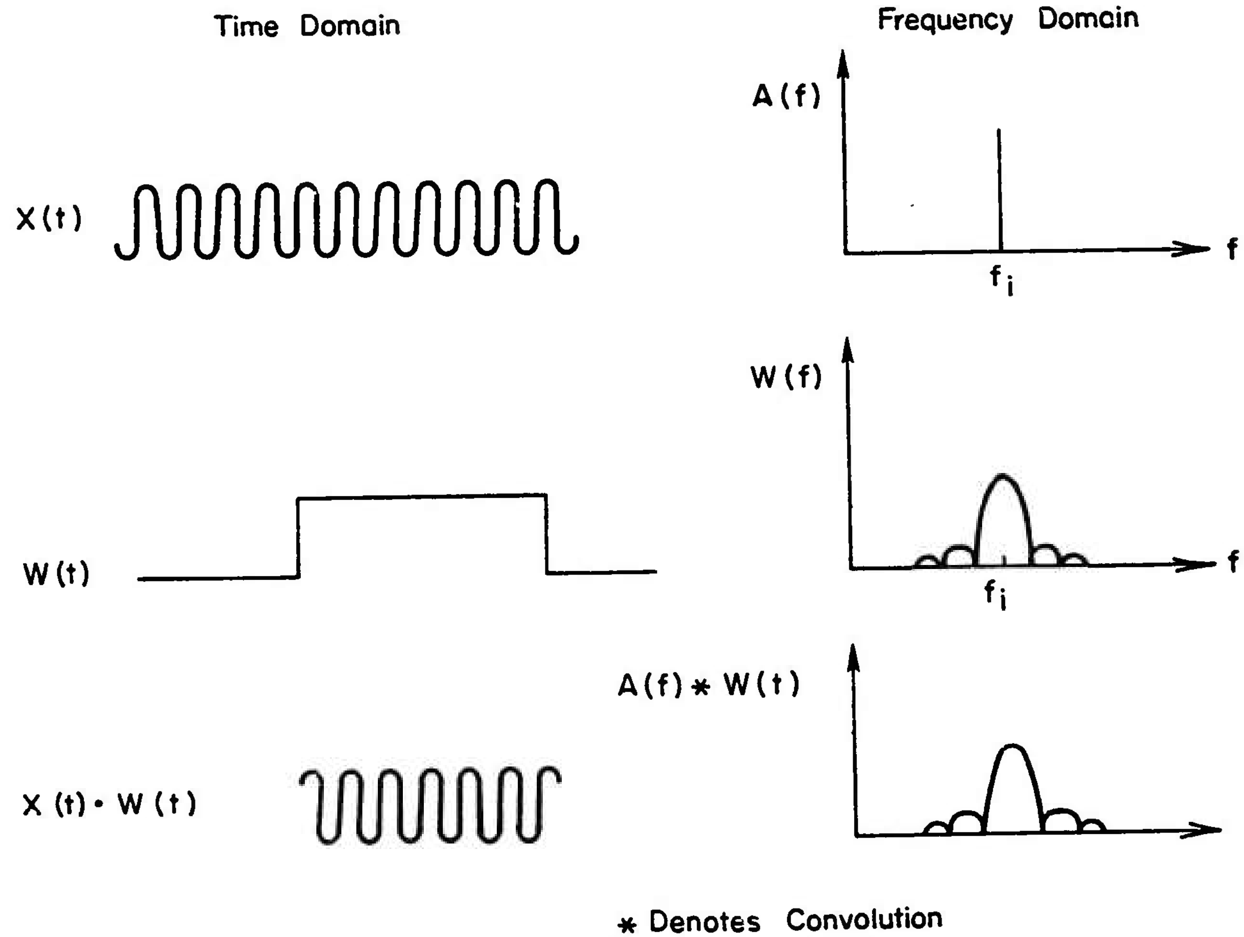


Figure 20. Leakage Characteristics.

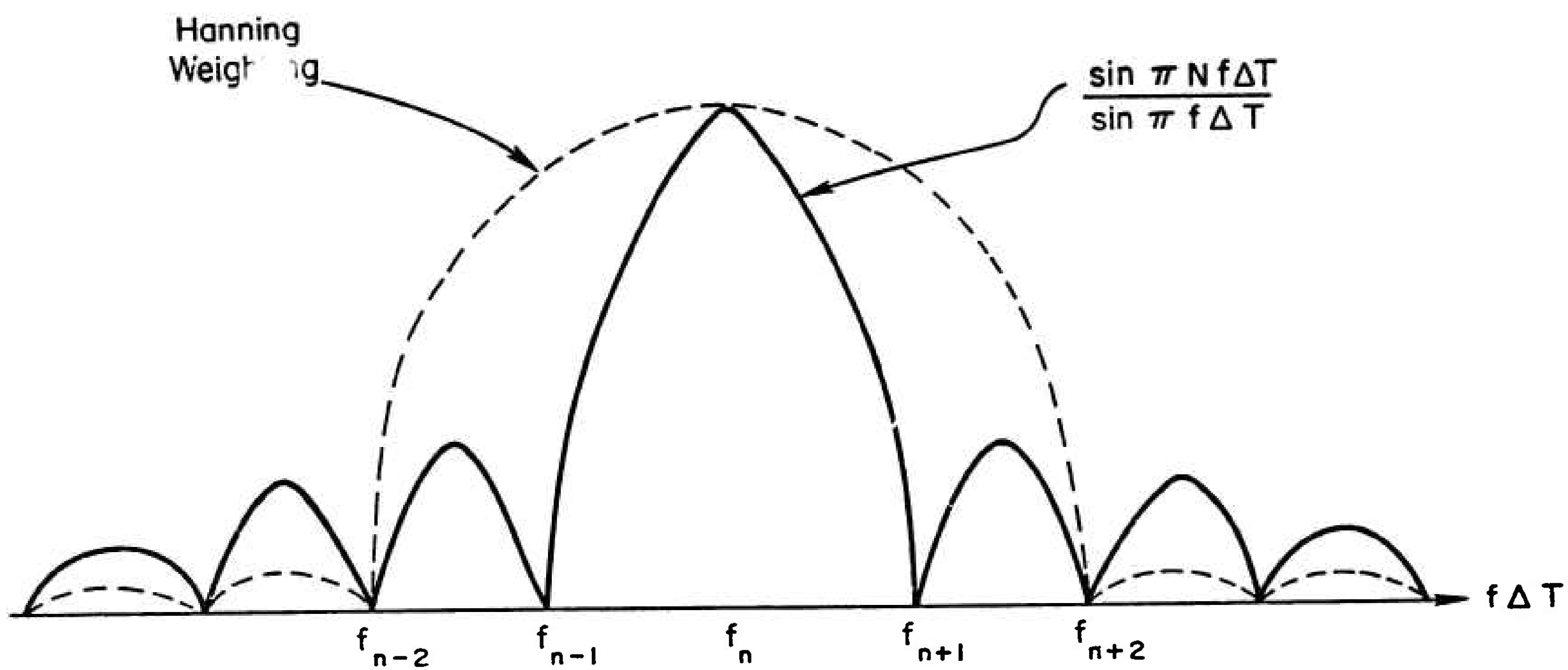


Figure 21. Effect of "Hanning".

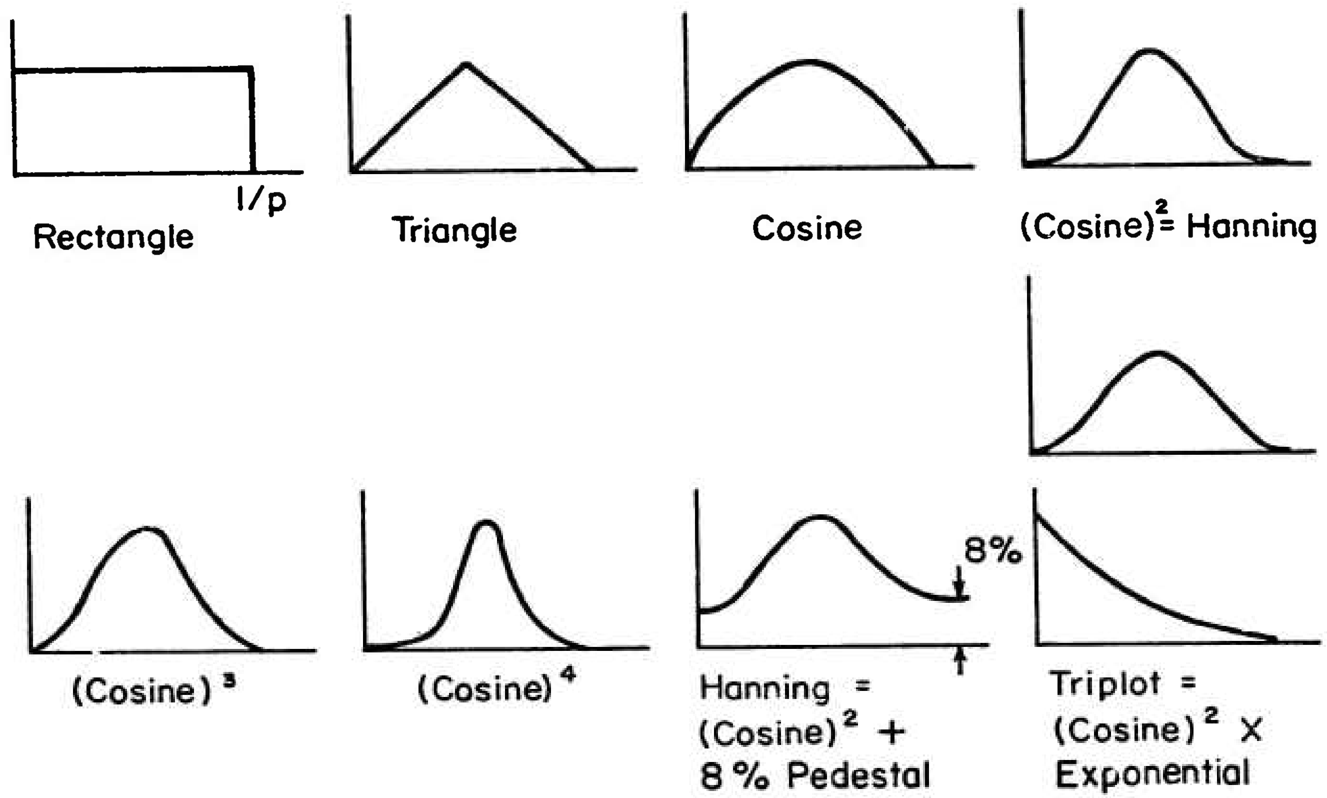


Figure 22. Weighting Functions.

3. Perform multiplication of $X_n(\cos\theta_n), X_n(\sin\theta_n)$

4. Perform summation

This calculation procedure will require approximately N^2 calculations. The frequency resolution is a function of N:

$$f_r = \frac{1}{N\Delta t} \tag{56}$$

where f_r = effective bandwidth. An enormously large computing burden is encountered and in this format the Fourier transform becomes expensive.

However, the development of the Fast Fourier Transform algorithm has greatly diminished this problem. While a development of the algorithm would be superfluous here, a brief description of the kind of savings it performs might be of interest.

The manner in which the computation savings are achieved may be illustrated with the use of the following equation:

$$a(b + c) = a \cdot b + a \cdot c \tag{57}$$

If this operation is performed in the following manner: add b and c, then multiply the sum by a, one multiplication and one addition are required. If instead, the multiplication of a times b and a times c are done and that sum added, two multiplications and one addition are performed. The first mode of operation saves a multiplication and, in terms of computer operation, almost halves computation time.[33] This distributive-type operation is, in essence, what the FFT algorithm does. In terms of time savings, an approximation may be used where the speed ratio S.R. is the ratio of computing time via standard Fourier Transform to FFT.

$$S.R. = \frac{N}{4_i \Sigma r_i} \tag{58}$$

where r_i = prime factors of N. For example, if $N = 28 = 2 \cdot 2 \cdot 7$, $r_1 = 2$, $r_2 = 2$, $r_3 = 7$.

If the number of input sampled data points are constrained to be a function of 2, $N = 2^P$, where P = some integer, all calculation of expontials in the transformation are eliminated and further computation savings are achieved. This is the form of the algorithm which is used in most processors.

Fast Fourier Transformation processors use an A/D converter on the input and either a mini-computer, which is programmed to the algorithm, or hard-wired digital circuitry designed to perform the calculation.

Their capabilities are a function of the processing mode, i.e., hard-wired analyzers are generally faster. Computations are generally performed in a few seconds and are comparable to real-time analyzers in a frequency range up to 50 kHz.

The power spectrum is calculated directly from the Fourier coefficient

$$S_x(f) = \frac{2\Delta t}{N} |X(f)|^2 \tag{59}$$

Other frequency domain characteristics are similarly calculated from the Fourier coefficients.

Walsh Functions

Some consideration has been given to using a Walsh Transform rather than a Fourier Transform, i.e., expanding terms of Walsh functions rather than exponentials. The Walsh function has a sal and cal component analogous to the sine and cosine of the exponential. An example of Walsh functions is seen in Figure 23. The values are always either +1 or -1.[34] The transform into the Walsh domain would not require any multiplication by weighting functions; the only operations would be addition and subtraction.

In using Walsh transformations, the ordinate is sequency or the generalized frequency since the analysis is not tied to sinusoids.

Comb Filtering

In the case where the energy of a signal contained at the fundamental frequency and all harmonics is desired, digital characteristics may be used in a "comb" filter which utilizes the aliasing or fold-over characteristics of digital processing.

As seen in Figure 19, a digital frequency response is a continuous superposition with a folding over about the sampling frequency and its multiples. If designed as shown in Figure 24, the comb filter may be achieved. Here a digital band-pass filter is used. Sampling frequency is set at the fundamental of the desired frequency. Thus, fundamental frequency energy, as well as the "aliased" energy due to the harmonics, is passed through the filter. By changing sampling rates, different fundamental frequencies may be chosen.

An analog mechanization of a comb filter is possible as shown in Figure 25.

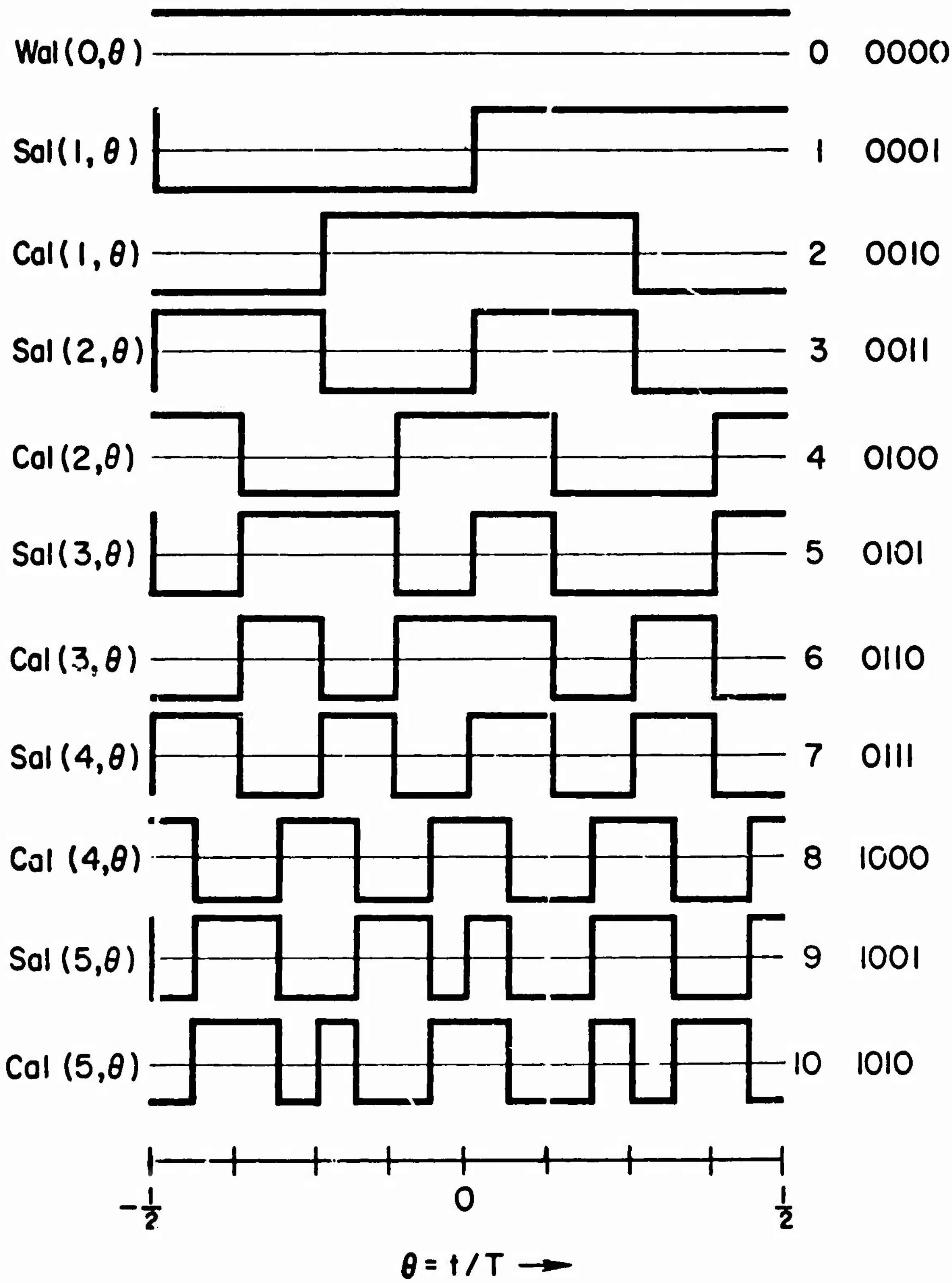


Figure 23. Walsh Functions.

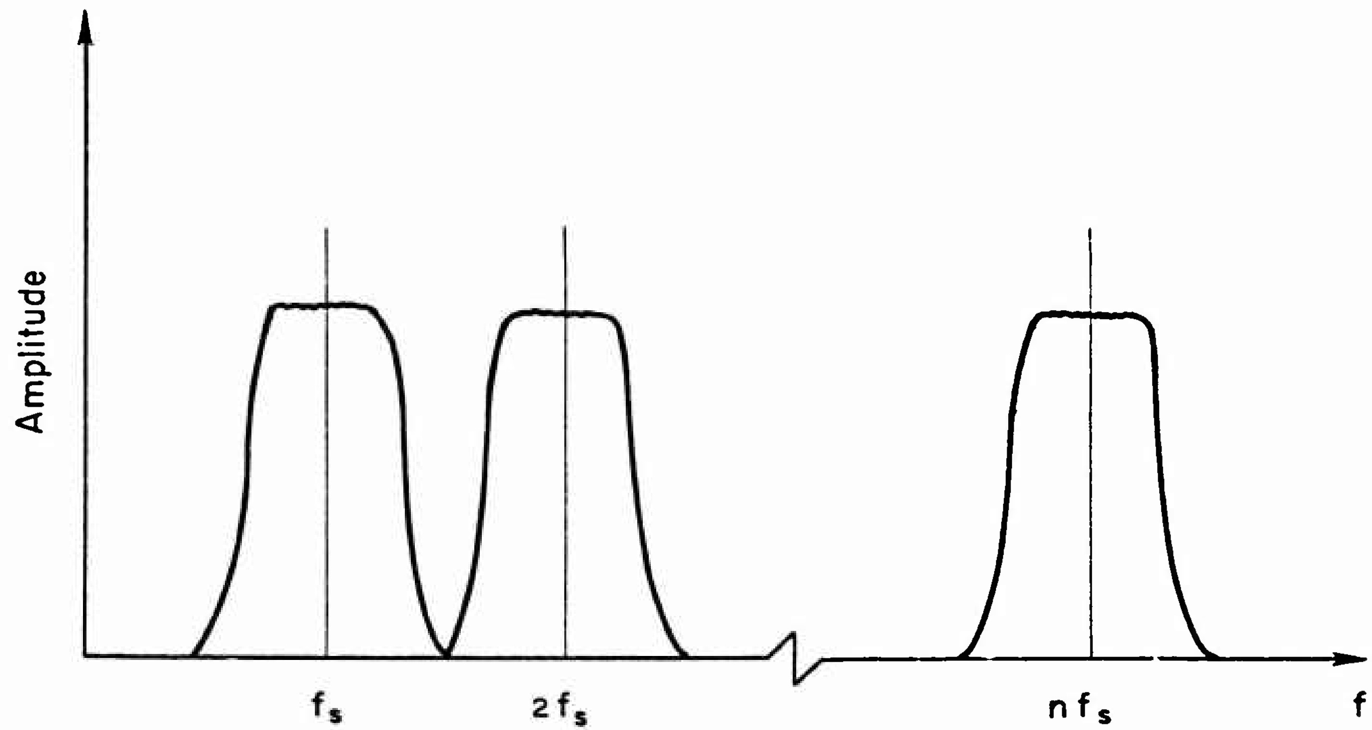


Figure 24. Frequency Response of a Digital Filter.

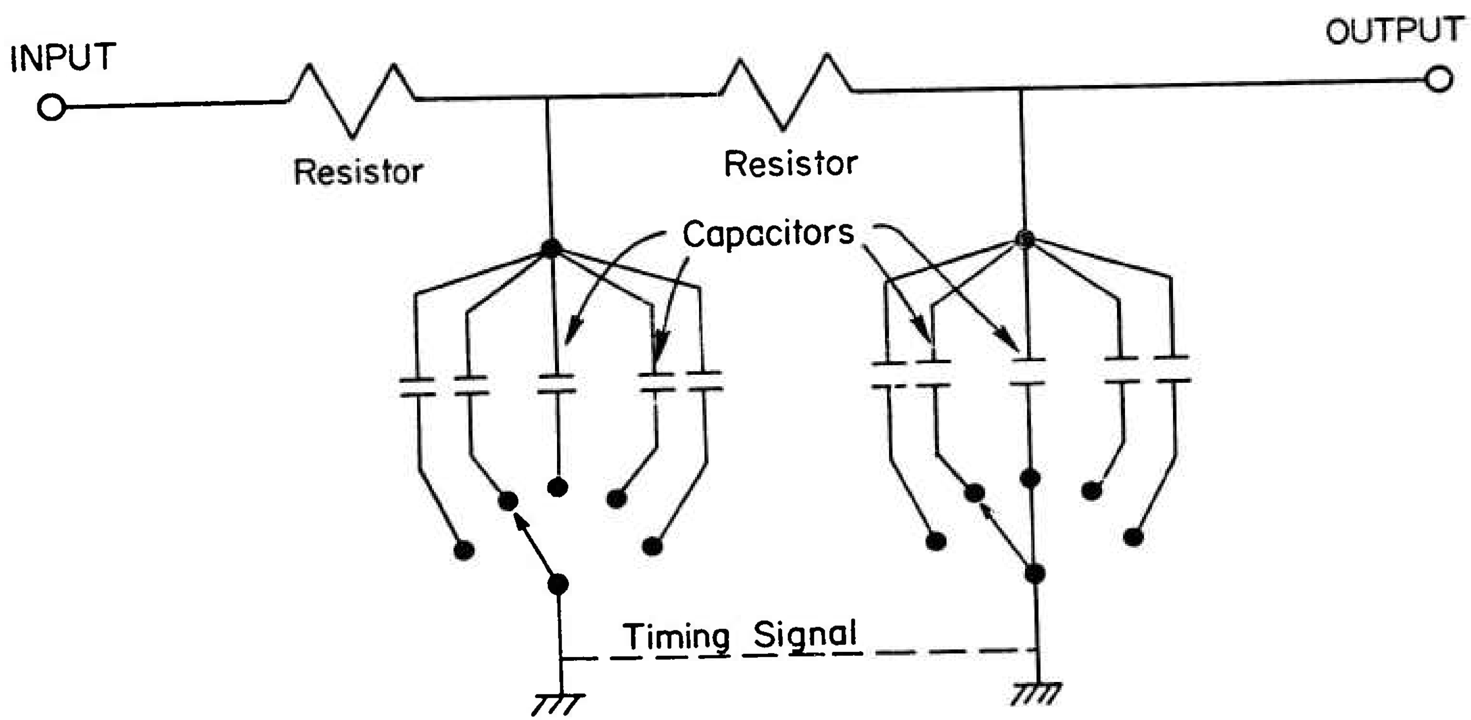


Figure 25. Analog Comb Filter.

The number of harmonics of the sampling (or clock) frequency which is passed is equal to the number of capacitors used or, in other terms, the number of stages of the filter. This filter effectively performs time averaging.[35]

GENERAL DIAGNOSTIC PROCEDURES

In this section, the overall diagnostic problem including short discussions of transducers, data analysis techniques, and potential discriminants for differentiating between good and faulty components will be discussed. Means of normalizing data will be discussed, as will the general pattern recognition approach. Problems which are peculiar to helicopters will be interjected.

The number of possible types of diagnostic systems is indeed endless. The number of means of reducing time series data is very extensive. Then including the different types of transducers, the different transducer placements, and the different means of analyzing the reduced data, it can be seen how the number of diagnostic possibilities becomes large. This section will be general in nature, as specific techniques will be discussed in a later section.

GENERAL DIAGNOSTIC SYSTEM

As illustrated in Figure 8, a generalized diagnostic system is composed of a sensor, a data-gathering and -reduction facility, analysis of the reduced data to evaluate discriminants, and comparison of discriminants to ascertain the condition of the device being tested. In an effort to obtain an overview of many of the systems which are possible for vibration diagnostics, a block diagram of potential diagnostic systems and techniques is shown in Figure 26.

This diagram will be discussed in individual sections, with primary discussion centering around the transducers, their location, the mode of taking data, and the discriminants which result. In all of these discussions, it should be realized that there is no one best technique, transducer, or discriminant. For a given discriminant, one type of transducer may be required; while for another discriminant, the choice of transducer may be different.

Transducers

The most popular transducer used for vibration diagnostics work has been the piezoelectric accelerometer. The accelerometer has the advantages of being lightweight and easy to mount, has a wide dynamic range, and provides a strong self-generated signal which may be integrated to give velocity and displacement information. The accelerometer measures absolute motions and is not capable of measuring relative motions directly. Problems encountered with piezoelectric accelerometers include their inability to measure static motions and the requirement of special charge amplifier-type signal conditioning. They are also somewhat sensitive to transient temperatures. Accelerometers are available for measuring frequencies over 100 kHz. Typical accelerometer accuracy, under normal operating conditions, is ±1 dB over the operating frequency range.

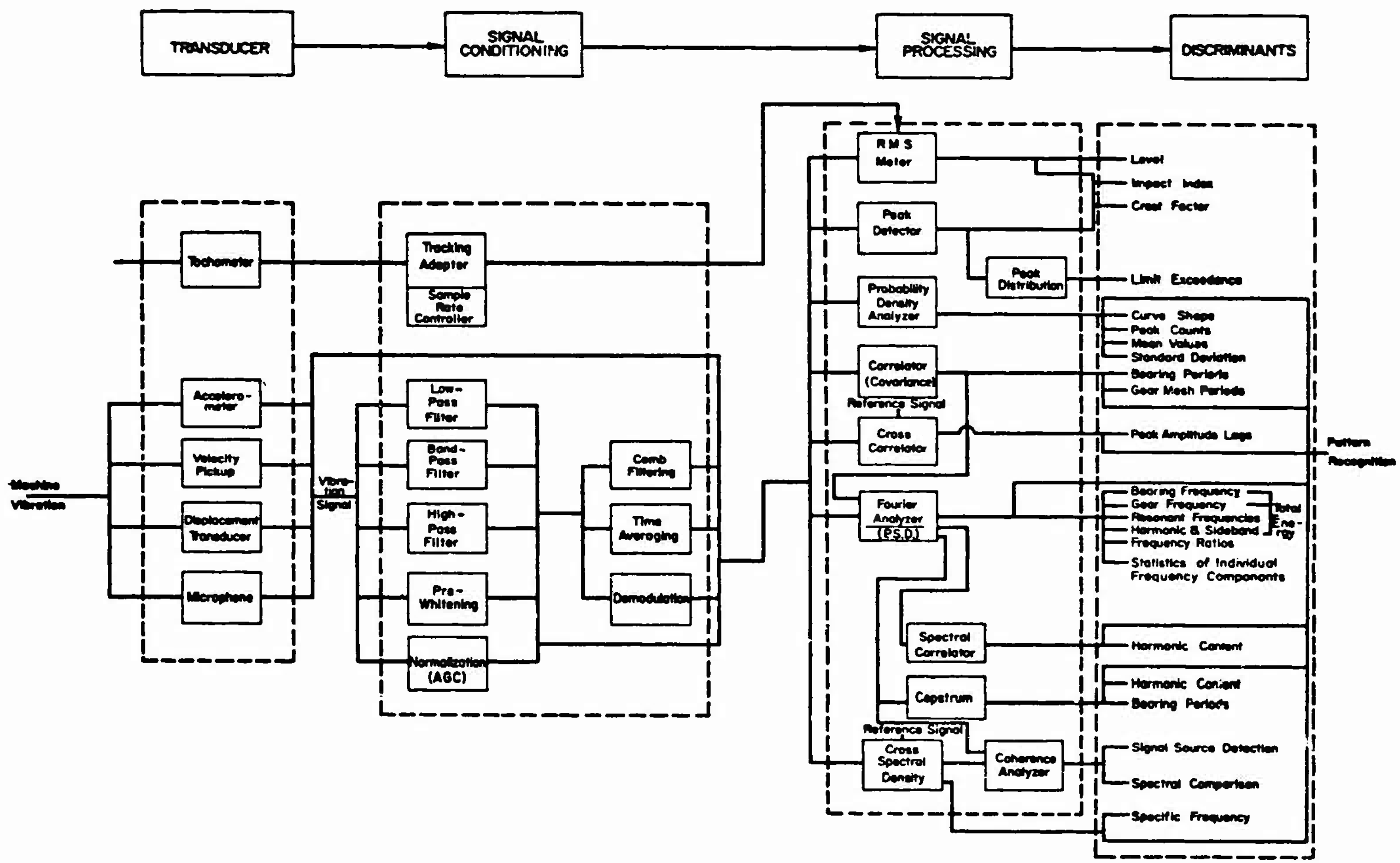


Figure 26. Potential Diagnostic Systems.

Seismic mass velocity pickups have received much use as vibration monitors on gas turbine engines. They provide a high output and do not require sophisticated signal conditioning. Velocity pickups are quite rugged but are physically larger than accelerometers. Relative to accelerometers, the dynamic range of velocity pickups is somewhat limited.

Noncontact pickups (typical of the capacitive, inductive, reluctance, or eddy current type) are used to measure relative displacements between two parts. Their primary use in diagnostics has been in measuring relative motion between bearings and shafts in heavy machinery where sleeve bearings are commonplace. One problem encountered in the use of these devices for measuring helicopter vibrations is the fact that they are very insensitive to high-frequency vibration and would be usable at shaft frequencies and their lower harmonics only. A primary reason for this is that displacement parameters favor the low-frequency end of the spectrum, whereas acceleration favors the higher end of the spectrum. Displacement measurements are the standard for determining shaft imbalance difficulties.

Since noise from a piece of machinery emanates from structural vibrations, the microphone can be considered as a form of vibration transducer. Microphones can be obtained with very high-frequency response ($>$100 kHz) and with varying degrees of directionality. They are exceptionally easy to mount, and because they may be multidirectional, they would appear to be ideal as diagnostic transducers. In fact, because of these fine characteristics, one diagnostic tool, the Curtiss-Wright sonic analyzer, has been extensively investigated for use in helicopter transmission diagnostics. One particular difficulty with microphone data is that the acoustics problems associated with microphone location, background noise, and the large number of acoustic inputs make the extraction of diagnostic information rather difficult.

It would appear that the piezoelectric accelerometer offers the greatest advantages for helicopter use. Based on data to be given later, it can also be shown that accelerometers tend to give a fairly flat frequency spectrum from 0 to 5 kHz. For helicopter data, velocity pickups tend to attenuate the amplitude of frequencies above 2 kHz, thus limiting the range of their use. Velocity signals can be obtained from accelerometers by simply integrating the accelerometer signal, but because of noise difficulties the differentiation of velocity signals to obtain acceleration is not as feasible.

Transducer Location and Mounting

Equally as important as the transducer itself is its location and the means by which it is mounted. Transducer location is often a function of the diagnostic discriminant being measured. For instance, some bearing discriminants require that the transducer be located on the bearing housing, whereas other techniques may have other critical location restraints.

One obvious deduction is that the transducer should be as close to the part or parts being monitored as possible. However, problems crop up when one desires to monitor more than one component with the same transducer. Here, it will be necessary to optimize transducer location in some manner. One means of doing this is to utilize the mechanical transfer function techniques discussed earlier.

In the helicopter, the number of transducers is a function of the number and levels of faults which one desires to detect. In the test bed program, the object was to ascertain the condition of line-replaceable units (LRU's), with little concern being given to fault isolation of individual gears and bearings. If possible, the ideal would be to have a single transducer for each LRU. In the case of the main transmission on helicopters, this would seem very optimistic since a typical main transmission (UH-1H as an example) contains over 20 gears and many bearings.

When locations of the transducers are determined, it is necessary to mount the transducers to the structures. The mounting technique can be very crucial, as a poor mount can result in both amplitude and frequency range losses. Typical means of mounting transducers include the use of (a) hand-held probe, (b) epoxy cement, (c) wax, (d) steel stud, (e) isolated steel stud, and (f) permanent magnet. Figure 5.48 of Mechanical Vibration and Shock Measurements[36] shows typical accelerometer frequency responses for these types of mountings. It is noted from this figure that the best frequency response is obtained for the steel stud and wax mountings. The other mounting techniques resulted in downward shifts in the transducer's resonant frequency which reduced the transducer's dynamic range. Since wax is a very temporary mount which cannot be used at high temperatures, the steel stud is the advisable technique for helicopters. Still, care must be taken in preparation of the surface for monitoring the steel stud such that the accelerometer mounts flush to the surface. R. Misialek[37] has proposed a method where a carefully machined steel block is welded to the part to be measured to obtain a consistently flush transducer mount.

Mode of Taking Data

The speed and load conditions which are prevalent when data is taken can have a significant effect on the output readings from a diagnostic system. In a helicopter, one has several choices of test conditions when data may be taken. Two speeds are typically available: ground idle and operating speed. In addition to these two speeds, load is adjustable by controlling the flight condition, i.e., either light on skids, ground hover, steady climb, or high-speed level flight. Data for these conditions will be compared later. In general, it was found that the information available in each of these flight modes was essentially the same. The flight mode to be utilized is then only a function of the amount of data needed, the compatibility of test equipment to the flight mode, and the required frequency of occurrence of testing.

The applicability of different types of operating modes of diagnostic systems will have a considerable effect on the test mode used. If the

diagnostic equipment is to be portable and data is to be taken every few hours of flight time, it is likely that some type of ground run or hover test might be most useful. However, if the monitoring of parts is necessary at all times, the diagnostic system would have to be flown with the helicopter, thus allowing recording of data in all flight conditions. These tradeoffs have been extensively studied by Northrup in the AIDAPS Program.[38] In general, our investigators would tend to question the net conclusion of Northrup, which says that the system that flies with the helicopter is the most powerful diagnostic tool. Our experience has been that most mechanical failures which might be detected with vibration diagnostics are not instantly catastrophic and are, therefore, more amenable to testing periodically in ground run or hover conditions. The use of the hover condition allows one to run at nearly the same load and speed during every test. It also allows the use of portable instrumentation which can be shared with many vehicles and the connection of data directly into a central processing system, if necessary.

A final technique for data gathering which may be useful in diagnostics is the use of variable speed run-ups and run-downs. These transient speed changes allow the use of structural resonances to amplify certain input vibration characteristics. One problem with this mode is the difficulty in interpretating the nonstationary data which is produced.

Data Acquisition Processing Systems

Various approaches to data acquisition were also covered extensively in the AIDAPS study by Northrup. The type of data acquisition system depends largely upon the mode of diagnostic system being used (on-board or portable) and the type or processor being used (either small on-board, portable ground based or large-scale ground based). Processers depend primarily on the types of data reduction techniques being used and the discriminant complexity.

Data Analysis and Discriminants

Following the initial reduction of data by techniques discussed previously, various additional data analysis techniques are required to obtain discriminants which can be used to distinguish between good and bad parts. Figure 26 shows many of these analysis techniques and also lists some of the resulting discriminants.

A discriminant is defined as a single numerical value or set of numerical values which, when compared to some reference value or set, is capable of determining the condition of an individual part of LRU. The discriminant is the key to the success of the diagnostic system and must be capable of not only flagging bad components but also not diagnosing good components as being bad. Discriminant levels which are set to designate the faulty condition of a component must almost always be obtained from experimental data. The amount of data and the number of different types of tests required are largely a function of the statistical accuracy desired and the

amount of physical modeling upon which the techniques are based. The more completely a technique can be modeled physically, the less data required for verification.

Typical parameters which are related directly to physical phenomena are frequencies of bearings and gears, structural resonant frequencies, and harmonic and sideband frequencies. Even though these frequencies or related parameters are known and can be directly related to specific faults in gears and bearings, the means of analyzing and interpreting data related to these frequencies requires ingenuity in physical modeling and data processing. These same frequencies can be observed or manipulated by many mathematical techniques, including correlation, time averaging, and demodulation, in order to obtain different discriminants.

Other discriminants can be obtained from statistical reduction of the vibration data. Included here are the shape of the probability density function, peak value distribution, ratio of peak to RMS values, etc.

PATTERN RECOGNITION

Another means of obtaining discriminants is by the method of pattern recognition, where the mathematical functions for good and bad components are statistically compared. Parameters which are found to be statistically sensitive to faults in a given component are chosen to form a mathematical discriminant.

Pattern recognition has received a large amount of interest in the following areas: alphanumeric recognition, speech processing, medical diagnosis, antisubmarine warfare (ASW), radar and sonar identification, and fingerprint identification. In all of these areas the basic task is to separate and identify various patterns. The method of achieving this goal is the development of a classifier which statistically differentiates between classes of data with a high degree of statistical confidence. This task is typically done by applying a training set of data to the chosen classifier. In the case of a diagnostic system, this training set would consist of both good component data and data for all types of bad components. Sufficient data for each class of failure and good parts are necessary to obtain statistical confidence; sufficient, in this context, might refer to 10-15 different data sets for each failure mode. Likely parameters to be used in the classifier of a vibration diagnostic system are specific frequency bands from power spectral density functions or time lags from correlation functions.

Many pattern classification techniques have been used. Most are linear in nature. However, some of the more complex schemes may also classify in a nonlinear manner. Many of these techniques are discussed in Nagy,[39] Tou,[40] Mendel and Fu,[41] and Nilsson.[42] Some of the more common methods of linear categorization include maximum likelihood, correlation, minimax decision rule, Bayes classification, and discriminant analysis.

The first element in developing a pattern classification technique for a diagnostic system is the selection of parameters which are most indicative of a change in state of a particular component. In the frequency domain, these parameters may be amplitudes of given frequency bands, the ratio of amplitudes of bands, or the sum of amplitudes of several bands or any of a great number of other combinations or permutations of discrete frequencies in the vibration spectrum. The parameters are usually chosen on a statistical basis as the most likely parameters to differentiate between good and bad classes.

Once the parameters are selected, they are used in some form of classifier, which, as mentioned previously, may be of a linear or nonlinear nature. This classifier typically tries to fit the test data into the class which is statistically the most probable or, from the other point of view, the class which is least likely to be in error.

A typical pattern recognition scheme is shown in the block diagram of Figure 27.

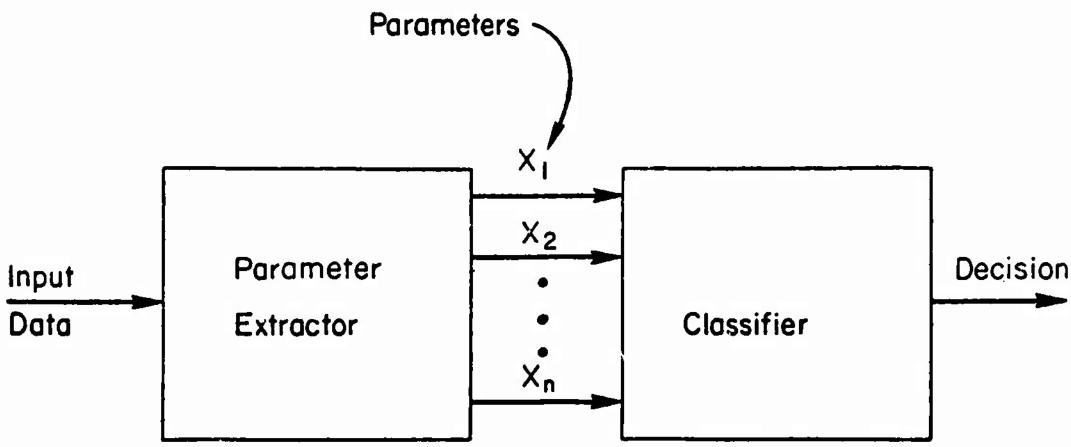


Figure 27. Typical Pattern Recognition Block Diagram.

One difficulty encountered with pattern recognition schemes is that they require an extensive amount of data to develop the classifier and determine its validity. An example of the reasoning forming this statement might be made by considering pitting in a gear as a failure mode. If the classifier is trained with pitch-line pitting, it is possible that the classifier might have difficulty in detecting pitting at other points on the gear due to the greatly different loading characteristics at these points. Therefore, the size of the required training set could become quite large.

NORMALIZATION PROCEDURES

Several types of normalizations may be applied in order to make the selection and use of diagnostic parameters less sensitive to speed and load

changes in a system.

Perhaps the most often used normalization in a PSD analysis is that of normalizing frequencies of rotating components whose speed tends to change with time. In the helicopter, for instance, it is difficult to compare vibration frequencies of two spectra taken at two different operating speeds since most of the predominant frequencies are determined as a function of speed. By normalizing the frequency axis to multiples of shaft speed or some other nondimensional feature, the changes in engine speed can be reduced considerably. The easiest means of normalizing speed is to simply plot frequency on a logarithmic axis. Then, by simply sliding one plot with respect to another, superposition of speed-related frequencies in the spectrum can be made. This technique does tend to compress frequencies in the upper ranges and is, therefore, little used in practice.

A more popular means of normalizing frequency effects is to control the sampling rate in digital schemes or to change the frequency sweep rate in analog schemes so that the frequency axis is normalized. Devices are available on most digital and analog frequency analyzers to accomplish this. One precaution which should be taken into consideration is that if the engine speed changes considerably (±5%), the effects of structural resonances may greatly change individual spectra.

A final means of assuring that speed change effects are insignificant is to take data only when speed is within a specific range. When the tests are of a controlled nature, as would be the case in a helicopter hover test, this may be possible. However, small speed variations may still be enough to slur frequency bands in a typical frequency spectrum. For example, a one percent speed variation of an engine will cause smearing across 4-5 frequency bands in the higher 100-frequency bands of a 500-line frequency analysis.

In taking correlation data, time lags must be normalized in a similar manner as with frequency. Since most correlation techniques are digital in nature, correlation functions can be normalized by controlling data sampling rates as a function of engine speed. This will eliminate smearing of correlation peaks across several time delays when averaged.

Normalizing loading conditions is not as straightforward as is speed normalization. Again the easiest safeguard would be to always record data at the same load. When this is not possible, a means of taking ratios of the amplitude of frequency spectra to obtain meaningful data is necessary. Ratio in the time domain may also be useful in normalizing loads.

SPECIFIC TECHNIQUES

Many companies in the process of analyzing diagnostic procedures, or while studying the dynamic characteristics of machinery componets, have developed techniques or discriminants which they feel have special merit. Based on their judgment of possible successful applications, they either have built systems which utilize these techniques or have proposed programs to develop the diagnostic capabilities of them. The development work has been of both the "in-house" variety to develop a diagnostic capability for a specific internal application and the type based on outside contractual obligations. A number of specific systems that have been built or proposed will be discussed.

The diagnostic techniques discussed here are in various stages of development. Some are being marketed as a product line and have undergone extensive testing. Others have been assembled as laboratory prototypes and have undergone some experimental verification. There are others which have not gone beyond the planning stage. The specific utilization employed by the various techniques discussed are quite diverse, with some being developed to monitor one specific machine element, i.e., gear, bearing, etc., while others will diagnose a complete machine's health, e.g., a helicopter transmission. The basis of the analysis procedure is quite varied. There are some techniques which are based on an analysis of the physical phenomenon which is occurring, while others utilize pattern recognition schemes.

An attempt has been made, on the basis of information available, to detail a number of basic points concerning each technique. First, of course, is the use to be made of the technique; i.e., does it diagnose gear failures, bearing failures, transmission failures, turbine failures, or any combination of these. Next, the developer or vendor of the system is identified as well as purchasers, if any are known. The physical phenomenon or mathematical technique which forms the basis of the analysis is then discussed. The processing mode is then covered, including the equipment used, the mode of operation, and the type of output which is produced. The testing and application to which this system has been put are discussed, and the final item is whether there are any special difficulties which may be encountered due to signal contamination by noise or variations due to speed or loading changes in the machine.

It is quite probable that all diagnostic techniques are not included here. Probable reasons for techniques not being included are:

1. The investigators in this study failed to identify a technique in their literature search.
2. Techniques of a proprietary nature were not made available to the investigators or, if made available, were not publishable herein.
3. Some systems are not diagnostic systems as interpreted by the investigators. This category includes advertised diagnostic

systems which are simply data reduction systems and do not determine any specific discriminant for use in diagnosis.

4. Many diagnostic systems are essentially the same and may all be classified under the title of general narrow-band analysis. The same basic analysis procedure is employed by all with the use of slightly different instrumentation and diagnostic hardware. A discussion of general narrow-band analysis as a group is included, with only a few specific systems mentioned for example purposes. Note is made in Appendix I if a company contacted had made use of narrow-band analysis as discussed in this context.

Since all of the techniques discussed have been developed by some company, they will often carry the company's name in their title. The techniques are listed in alphabetical order by the company name of their developers.

CURTISS-WRIGHT SONIC ANALYZER

This diagnostic tool was developed by the Curtiss-Wright Corporation for use as a condition indicator with gas turbine engines. Later, its capabilities were expanded to allow it to be used with other types of rotating machinery, e.g., transmissions and gearboxes. It is presently available as a package which may be purchased.

The analyzer makes use of acoustic signatures of the machine being analyzed. It has often been shown that the acoustic signals emanating from a machine are directly related to the vibration of the machine itself. The procedure consists of measuring the spectral content of specific frequency bands in the acoustic signal. These frequency bands are chosen to correspond to components of the machine monitored, e.g., ball bearing and race pass frequencies, turbine blade pass frequencies, shaft rotational frequencies, etc. The amplitudes measured in these bands are then referenced to amplitudes which were measured for "good" machines, i.e., those which were just overhauled or visually inspected. If the amplitudes measured exceed the reference amplitudes by a significant amount, the part may be judged as defective.[43]

Figure 28 shows a simplified block diagram of the workings of the analyzer. The input is supplied by one of three condenser microphones that may be manually selected. This signal is then fed in parallel through a phase-lock loop and a band-pass filter. The phase-lock loop is used to provide normalization of speed variations of the machine being tested. Some very strong spectral component, e.g., a blade pass frequency on a turbine or a gear mesh frequency on a transmission is used as a speed reference for frequency tracking. This reference is used to control the center frequency of a 15-Hz crystal band-pass filter. The center frequency is set at some multiple or fraction of the reference signal (which corresponds to the frequency of interest) through the use of a tracking adapter. The acoustic signal, after some initial conditioning, is then fed through the band-pass filter and the output of the filter is fed into a detector. The detectors read the amplitude of the frequency component on a 1-10 scale which is calibrated so that a "good" engine will register approximately 5.[44]

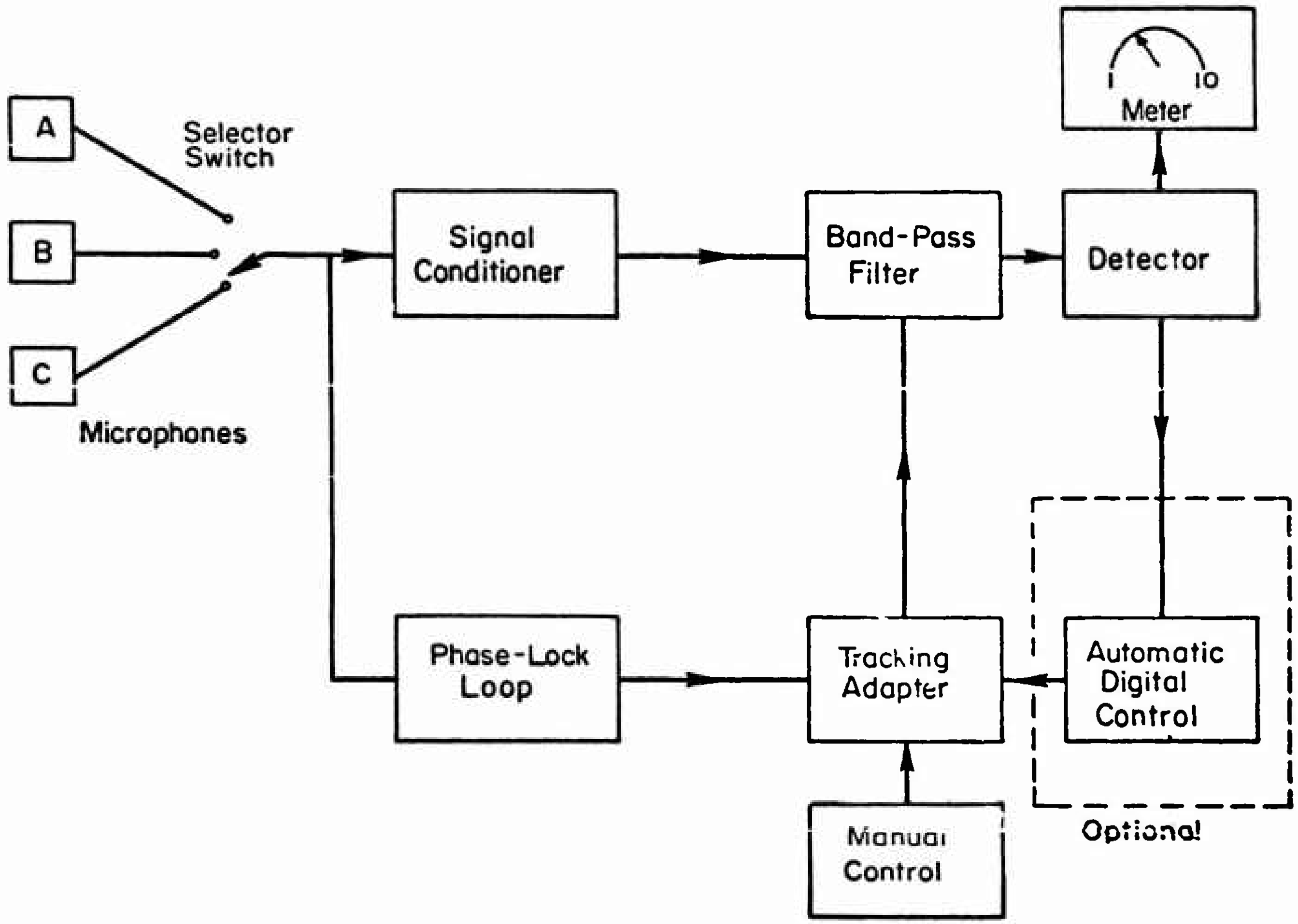


Figure 28. Block Diagram of Curtiss-Wright Sonic Analyzer.

The analyzer may operate in either a manual or an automatic mode. In the manual mode, the spectral components are selected by dialing in specific frequencies to be tracked. The output is then read off the meter. Thus, the operator cycles through the frequencies of interest to him and records the results. A paper tape system may be used as the automatic mode. In this mode, a tape is made which will cycle the analyzer through the desired frequencies. The detector output is read, and amplitudes which deviate significantly from the baseline are recorded on tape.

The results of interest are the measure of deviation of the spectral components from baseline amplitudes. By periodic measurement, the increase in this deviation may be followed as a component's condition degrades. The absolute amplitude which signals the necessity of component replacement must be provided for the operator through further analysis or testing.

The sonic analyzer was originally developed for use by the Navy to monitor jet engines. The Navy has been a primary user since that time.[45] The Army has also used the analyzer on both its UH-1 and CH-47 type helicopters.[46] Also, National and Eastern Airlines have bought units. Published results of the effectiveness of the analyzer run from 0% to 100% diagnostic accuracy with an average of 40%-60%.

The system may be used at various machine speeds due to the phase-lock mechanism and tracking adapter. It will hold the frequency ratios for speed variations to ±3%. However, the results are load sensitive and monitoring must be done under the same loading conditions each time. Extraneous noise appears to be a serious problem. Since nondirectional microphones are used, the analyzer will pick up background noise. In a testing environment such as a flight line, this background noise may include strong spectral components from engines other than the one being monitored.

NOISE-CORRECTED SPECTRUM ENERGY

This analysis procedure is directed solely at diagnosing the condition of the gears in the power train of a UH-1 helicopter. It was developed by engineers from the Curtiss-Wright Corporation for use with the sonic analyzer. The program was conducted in conjunction with an evaluation program performed at USAAMRDL, Fort Eustis, Virginia.

The technique is used specifically for gear condition monitoring based on the increased sidebanding and modulation which tend to occur in degraded gearing. An analysis of this effect was performed on acoustic signals produced by vibration of the power train and transmitted to a microphone. The parameters used to determine condition are the spectral amplitudes of the gear meshing frequency, the first upper and lower sidebands of the mesh frequency, and the first harmonic of the gear meshing frequency. These specific amplitudes were obtained by dialing in the desired frequencies on a Curtiss-Wright sonic analyzer and recording the amplitudes read off the meter.

A basic assumption made in this procedure is that amplitude levels of a given spectral frequency for a gear pair of the same mechanical condition vary linearly with the extraneous noise levels. Using this assumption, the following normalization procedure may be followed :

$$A_c(f) = C_1\ (1.5 - n) + A(f) \tag{60}$$

where f = frequency of interest
$A_c(f)$ = corrected spectral amplitude, dB
C_1 = constant
n = noise level, dB
$A(f)$ = measured spectral amplitude, dB

The noise level was determined by monitoring areas of the spectrum where no frequencies or harmonics related to power train components (gears, bearing, etc.) could be found. C_1 was found experimentally and refers to a given gear mesh, i.e., each gear mesh could have its own constant (C_1).

Once the amplitudes of the frequencies of interest for an individual gear mesh were found and the amplitudes corrected for noise, the amplitudes (in decibels) were added. This decibel amplitude was used as the discriminant. If the summed amplitudes exceeded limits set by the experiment, the gear was judged to be faulty.[47]

It is interesting to note that in the normalization procedure, decibel amplitudes are being multiplied by constant factors. This is not the same operation as multiplying actual amplitudes. It is, in fact, a non-linear procedure. Also, in the analysis, amplitudes in decibels are added, which has the effect of multiplying the actual amplitudes level together.

As developed, the technique utilized the sonic analyzer in its manual mode of operation and the corrections and calculations were performed manually. However, the same procedure could be performed automatically if the analyzer's automatic mode were implemented.

The specific procedure was developed using data taken from helicopters whose condition was known. However, no further testing was performed on helicopters with unknown gearing conditions. All of the data which was available was used in the development of the system, i.e., calculation of constants and setting of limit values. With this data base, the analysis procedure proved 100% effective. However, as mentioned previously, testing was not extended to any vehicles outside the training set.

Due to the normalization hypothesis, this technique should be usable on any helicopter despite background noise characteristics. Speed changes in the system should have little effect on the results due to the phase-lock loop inherent in the sonic analyzer. Since analysis did not extend outside the training set, the effect of varying load is unknown.

CORRELATION ANALYSIS

This procedure has been proposed by Ensco, Inc., of Springfield, Virginia, for use in diagnosing the condition of helicopter power trains. It contains two procedures: one for use on bearings and one for use on gears. The bearing procedure makes use of time-domain correlation, while the gearing technique makes use of correlation in the frequency domain.[48]

The procedure for bearing failure detection utilizes the autocorrelation function. By observing the peaks having time lags corresponding to the periods associated with specific bearing components, a judgment on a specific bearing failure is made. A procedure which Ensco calls "stochastic correlation" is used in computing the correlation function. According to Ensco, this procedure has the capability to adjust the analysis to negate the effects of speed fluctuations in the helicopter. Bad part baseline data is used to deduce limit values for the correlation amplitudes.

The gear detection technique is based on the fact that as gear wear or other failure modes occur, the vibration signal becomes increasingly rich in harmonic content. The first step in the analysis is to develop a set of "good" and "bad" baseline spectra of the vibration signals. To help amplitude normalize these spectra, pre-whitening is suggested. To determine the condition of a helicopter, a spectrum of the vibration signal is obtained and a spectral correlation with the baseline data is calculated. If the signals are related, peaks in the correlation function should be seen at frequency shifts corresponding to the frequency difference between harmonics of the gear mesh frequency in the signal. A statistical measure of the extent of correlation will be found and used as the discriminant.

The technique, as presented, uses entirely digital processing. The signals from accelerometers mounted on a helicopter or a microphone on the ground would be fed into a ground-based digital computation system which would analyze the data and provide the results.

This diagnostic procedure was presented as a proposed program. The mathematical procedures have been used in various pattern recognition work for vehicle identification, antisubmarine warfare, etc., but application to condition monitoring has not been made.

Ensco expects that the processing procedures outlined here are powerful enough to overcome noise difficulties. Speed variations will be accounted for by using logarithmic speed axes which could be shifted to provide compensation. The results of these procedures, as well as loading effects on the analysis, are not known because of the lack of verification testing.

COMPOSITE EXCEEDANCE

This diagnostic technique is a statistical procedure to be used for condition monitoring of any type of rotating machinery. It has been developed by Airesearch Manufacturing Company, The Garrett Corporation under a

prognosis research program sponsored by Eustis Directorate, USAAMRDL (report not yet available).[49]

The technique is based upon the amplitude distribution of the peak values of acceleration of the system being monitored. It is hypothesized that in the case of normal operation, i.e., "good" operating condition, the peak value amplitude distribution will exhibit Gaussian behavior. However, when a fault occurs, the distribution tends to change shape. If the fault is not too severe, the distribution may still look Gaussian but will have larger means and standard deviations. If the fault is severe enough, the distribution may appear to have a non-Gaussian shape. (See Figure 29.)

To be implemented, reference distributions must be acquired. Since most physical data is somewhat nonstationary, a set of these distributions will fall into a band. This reference band will be used as the "good" condition case. Significant deviation from the reference band will be used to signal a degraded component condition.

The generation of amplitude distributions is performed digitally. It involves the digitization of the acceleration signal, quantization of amplitude bands, and the counting of peaks occurring in each band. The distribution can then be obtained in the following manner:

$$N(\xi_i) = \frac{M_i(\xi_i)}{M} \qquad (61)$$

where ξ_i = amplitude level

$M_i(\xi_i)$ = number of peaks occurring in the band about ξ_i

M = total number of peaks

In the case of nonstationary operation, i.e., varying speed or operating conditions, a weighting is used to get a weighted average exceedance:

$$N_w(\xi_i) = \frac{T_j}{T} N(\xi_i) \qquad (62)$$

where $N_i(\xi_i)$ = weighted distribution value

T_j = time of operation at condition j

T = total time of operation

The results produced will be the peak amplitude distributions. As described, the determination of good or bad condition must be made by the system operator on the basis of change in distribution shape or deviation from the reference curves.[49]

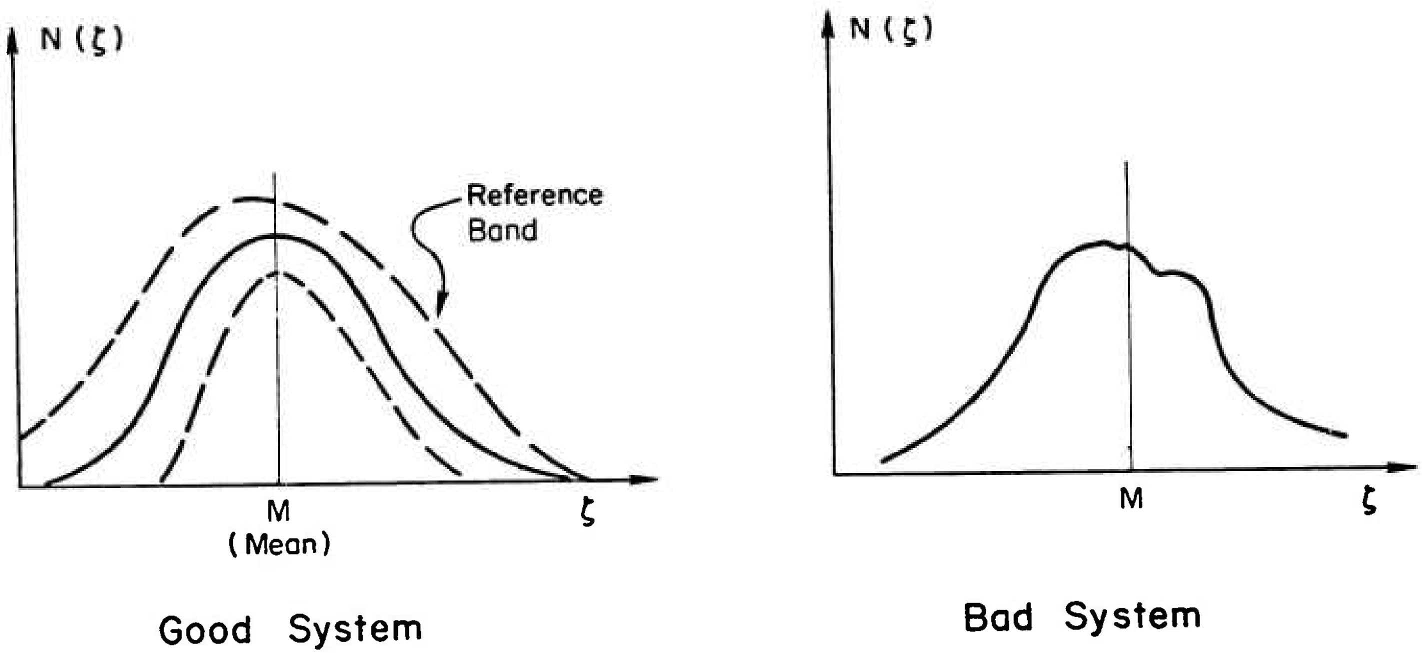


Figure 29. Typical Amplitude Distributions as Used in Composite Exceedance Technique.

According to the information at hand, no great amount of testing of this technique has been performed.

It is expected that load and speed variations in the monitored system should not present great difficulty because of the weighting characteristics. The amount of extraneous noise could provide a problem. If overall signal levels are significantly greater than those caused by the degraded part, the amplitude distribution change could be buried in the signal. This statement is simply conjecture because of the lack of testing.

LIKELIHOOD ANALYSIS

This diagnostic procedure is a statistical pattern recognition technique developed in conjunction with the TEDS (Turbine Engine Diagnostic Systems) project for the Air Force Aero-Propulsion Systems Laboratory, Wright-Patterson Air Force Base. The work was performed by Airesearch Manufacturing Company of the Garrett Corporation.[50]

The technique is based on the statistical characteristics of the vibration signal and is a variation of the likelihood recognition technique as it is generally known in the pattern recognition field. In this case, the vibration signal, which ranged from 0-26 kHz, was divided into 128 partitions each having a 200-Hz bandwidth. A large amount of data was gathered both for engines in "good" condition and for those containing failures. Based on this data, amplitude distributions were produced for each of the 128 partitions or parameters of the analysis. This information provided the baseline reference for further use.

When an engine of unknown condition is monitored, the amplitude of each of the 128 parameters is found. The probability of this parameter's lying in the "good" category as well as the "bad" category is found. The Likelihood Index of that parameter is then formed by taking the ratio of the probability of indication of a failure to the probability of "good" condition. An index value greater than one shows a greater probability of failure than of "good" condition. Figure 30 shows a typical result for one parameter. In a general sense, any monotonic function of the two probabilities may be used, such as differences, sums, weighted ratios, etc.

A spectral analyzer or band-pass filter is required in developing the reference distributions. The operation is probably easiest to perform in a total digital manner using a computer. Once the reference distributions are found, the total analysis may be automated with a bank of band-pass filters or a swept-frequency filter and logic circuitry.

A diagnosis of failure is made on the basis of the values attained for the Likelihood Index. Limit values are set for the index number for each of the parameters. Based on experimental work, it was found that if a given number of parameters have index values which exceed their limit values, a diagnosis of failure can be made.

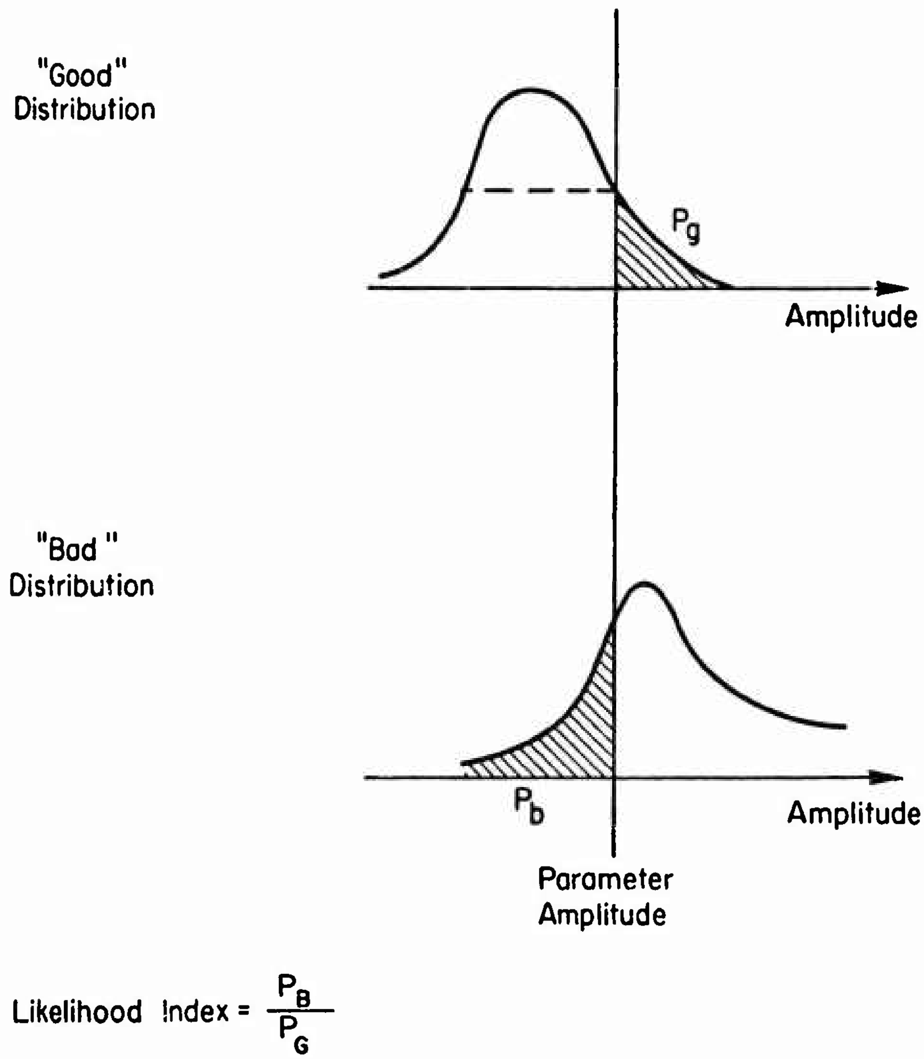


Figure 30. Typical Calculation of Likelihood Index for One Parameter.

A screening procedure is used to eliminate the effect of some of the statistical variations in the data. A number of index values for each parameter are calculated, either by taking more than one set of sample data or by using more than one reference data set. An index value for a given parameter is considered to be an indicator only if all the values calculated using the various data sets exceed the limits.

With spectral windows being used as indicators, the analysis will show a sensitivity to speed variations. Either the spectral analysis must consider this condition or the tests must always be run at the same speed conditions. The effects of loading variations and noise in the system are not entirely clear because of the lack of testing. A faulty bearing provided an interesting result: all parameters with large index values turned out to be at the bearing frequency or one of its harmonics.

BEARING IMPACT INDEX

This analysis procedure has been developed by the General Electric Company under the names impact index or crest factor. It is designed to monitor bearings and has been implemented in numerous applications, one of which is in the TF-34 analyzer.

The basis of this technique is the impact phenomenon which occurs in a bearing when a discrete fault appears. In monitoring the acceleration of the bearing, a periodic peak is seen to occur in the time signal. As the discrete fault becomes worse, the amplitude of this peak grows. However, the average (RMS) value of the time signal is affected little since the peak is of short duration. A ratio of peak acceleration amplitude to the average amplitude is formed and is called the crest factor.[51] In the case of the TF-34 analyzer, the ratio of half the peak to the average value is defined as the impact index.

$$\text{Impact index} = \frac{\text{Peak acceleration}}{2(\text{RMS acceleration})}$$

Experimentally, the following ranges of the index have been found to be indicative of bearing condition: 2-3, normal bearing; 3-8, spall initiation; 8-10, growth of spall. It has been found that after the index reaches about 10, further bearing degradation causes the index to decrease. The spalling spread all over the bearing surface after this level of spall occurred, which caused the RMS acceleration levels to rise significantly, thus reducing the index values.[52]

To properly implement this diagnostic system, an accelerometer is required for each bearing to be monitored. A single analyzer with a multiplexer may handle a number of bearings. A flow diagram of the analyzer used in the TF-34 system is shown in Figure 31. The acceleration signal passes through an AGC (automatic gain control) device and then through an average

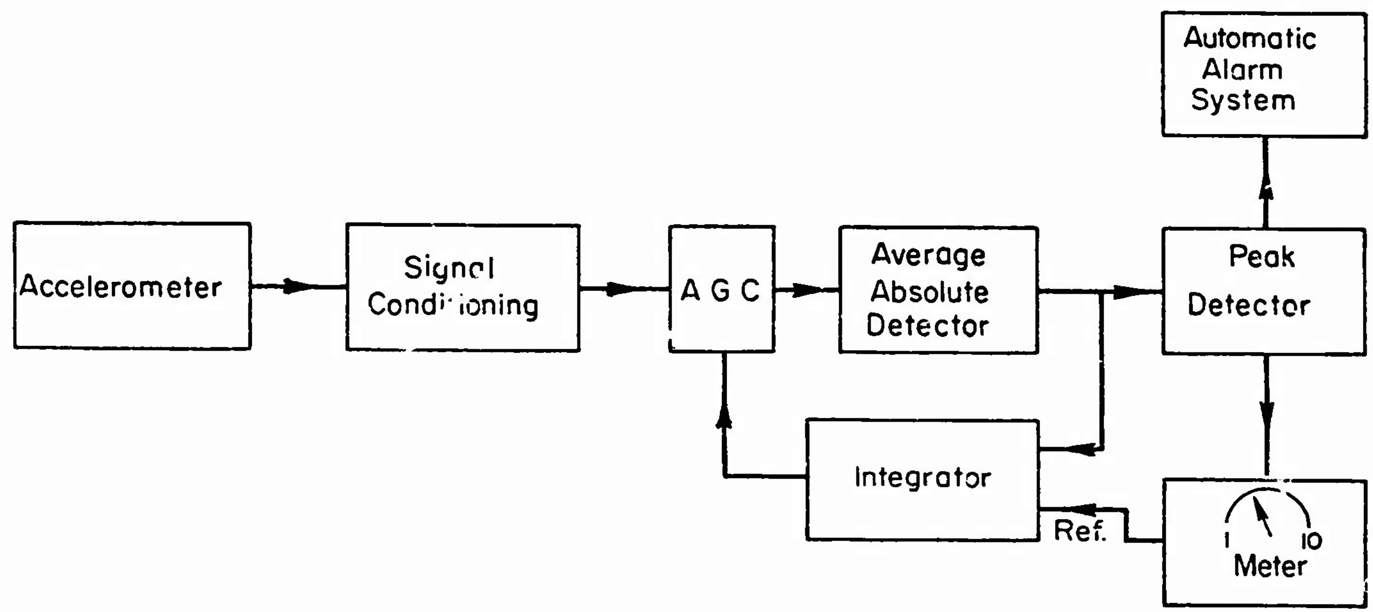


Figure 31. Block Diagram of Impact Index Detector.

absolute detector. The averaged signal is then compared to a fixed reference, and the error signal is used to control the gain. When the average is equal to the reference, the gain stays constant and the output is monitored for peaks. This peak reading is proportional to the impact index since the average value is always kept constant. This value may be read directly off the meter, or the signal may be used in an automatic system to trigger an alarm.

General Electric Co. has done testing work with the crest factor and impact index (both names have been used) for the Air Force and Navy as well as for industrial concerns and internal use. Some of the Air Force work, which concerned monitoring antenna bearings, was quite successful.[53] Their TF-34 analyzer was used on a TF-34 engine mounted in a Navy test cell. A crest factor meter is also being marketed.

Background noise is one problem associated with the impact index analysis. If the overall system noise levels (where noise is considered to be both discrete frequency and broad-band vibration from everything other than the bearing being monitored) are much greater than the peaks being produced by the bearing faults, the faults will not cause a significant increase in the impact index. In these cases, time averaging has been used with the impact index.[54] This procedure has proven successful but is very sensitive to speed variations and requires accurate speed synchronization. Loading does not appear to have too much effect on the analysis, as the ratioing tends to normalize loading effects.

FREQUENCY OF BINARY WORDS (FOBW)

This diagnostic technique is a pattern recognition scheme developed in conjunction with the "Data Analyzer" developed by the Electronics Laboratory of the General Electric Company. It was used both for "in-house" projects and with some analysis work for the Navy.

The FOBW analysis uses sonic or vibration data from a piece of rotating machinery. The first step, upon receiving the data, is to define an encoding algorithm. The processing is in a binary digital format, and the data must be put into this form. Thus, an A/D(analog-to-digital) converter which is programmable is used to reduce the analog signal to a string of 1's and 0's. Polarity coding algorithms have been used, assigning a 1 or 0 to the input point depending upon whether it or its slope is positive or negative. The type of encoding algorithm used will depend in large part on the baseline data which is generated in the design of the system.

Once the coding is done, binary words must be defined. These words are strings of 1's, 0's, and M's ("don't care" bits). "Don't care" bits signify that the word is the same no matter what bit fills that space. For example, the word defined by 1-M-M-0 may be written as 1-1-1-0, 1-1-0-0, 1-0-0-0, or 1-0-1-0. Once the words are defined, the frequency of occurrence of these words in the incoming vibration signal is found. For example, if we defined our word of interest as 1-0 and the incoming data string for 1 second looked like

1-1-0-1-1-1-0-0-1-0-1-0-0-0-1-1-0-0

the frequency of occurrence of the word would be six times per second.

Based on the words selected, various characteristics of the incoming data may be discerned. A few definitions which will prove useful are:

P = Length of the binary word in bits
n = Number of active bits in the word (those that are not "don't care" bits)
f_s = clock (sampling) rate of A/D converter
$f_o = f_s/P$

Words which begin and end in the same bit are called even, e.g., 1-0-M-1, 0-1-0, or 1-M-M-1. Words which begin and end in different bits are called odd, e.g., 1-0, 1-1-M-0, 0-1-0-0-1.

The binary word analysis now makes use of the frequency characteristics peculiar to it. If a sinusoidal test were run with frequency of occurrence of a given word as the amplitude measure, frequency response as seen in Figure 32 would be found. Three statements can be made about the frequency characteristics from this figure:

1. A cyclic filtering characteristic is obtained from the analysis (comb filtering effect).

2. The points of maximum response are a function of f_o and may be found in the following manner:

$$f_{max} = \begin{cases} n\, f_o & \text{odd words} \\ (n + .5)f_o & \text{even words} \end{cases} \qquad n = 0,1,2,\ldots$$

3. Frequency selectivity is a function of the number of active bits in a word. If the bandwidth (BW) is defined as the half-power level of each peak,

$$BW = \frac{f_o}{2(n - 1)}$$

It has been found experimentally that there is an amplitude sensitivity. If the amplitude of an incoming spectral component is large, the frequency of the given binary word will be large. And, as long as the signal-to-noise ratio is less than one, increasing the bit size of the word will increase this amplitude sensitivity.[55]

Based on the characteristics which were described, an analysis procedure could be implemented. Binary words would be chosen in order to use their frequency characteristics in a type of frequency analysis. For example,

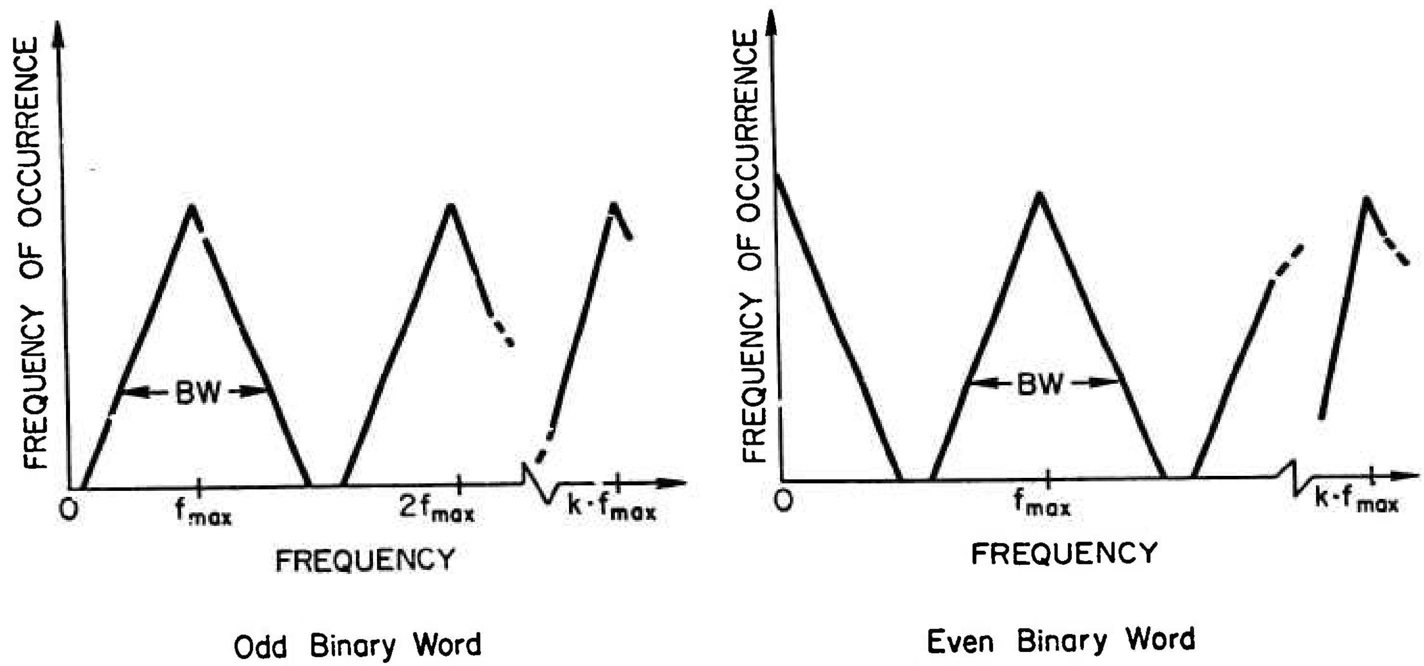


Figure 32. Typical Frequency Response of Binary Word.

to detect an inner race malfunction, the binary word would be tuned to the inner race-pass frequency. The choice of encoding algorithm would depend upon baseline data. The hardware used is shown in Figure 33. A programmable A/D converter puts the incoming data in the form of binary strings based on the sample rate and encoding algorithm. These strings are fed into a shift register equal to the length of the words being detected. The register is tied to the same clock mechanism as the converter. The output of the register goes into logic circuitry, which counts the frequency of occurrence of the given words. An output is provided which triggers an alarm at limit levels determined by previous testing.

General Electric has tested the FOBW analysis procedure to detect failures in rotating machinery with the effective filtering used to monitor the frequency corresponding to various gears and bearings. It was used on an American Airlines jet engine in overhaul as well as on various Navy engines. It could discern a spalled bearing but had difficulty because of spurious signals.[56]

A major difficulty is found with noise contamination of the signal. The "jitter" or "hash" on a signal can cause encoding errors and, thus, incorrect frequency counts. Speed variation in the monitored system can be handled quite easily through tachometer control on the A/D converter. It is unknown whether load variations would cause a major difficulty, but because of the amplitude sensitivity, it is expected that problems could occur.

GEAR DISCRIMINANT ANALYSIS

These techniques were developed to diagnose gearing failures. The General Electric Company developed the analysis techniques in conjunction with two programs: the TF-34 analyzer to be used by Naval Air Systems Command on turbine engines and a second Naval Air Systems Command project to diagnose failures in helicopter power trains.

The three gear discriminants utilized in these programs are all based on the deviations from pure sinusoidal mesh frequency vibration caused by faulty gears. If a failure is present in a gear, these deviations from perfect operation will become quite apparent as harmonics of the mesh frequency and sidebands of both the mesh frequency and its harmonics. The three discriminant values used were:[57]

1. Ratio of peak value of vibration signal to the average value.

2. Ratio of total energy content at the gear mesh frequency's harmonics to the fundamental.

3. Ratio of total energy contained at sidebands to that contained at the mesh frequency.

All three discriminants are implemented in the TF-34 analyzer system as shown in Figure 34.[58]

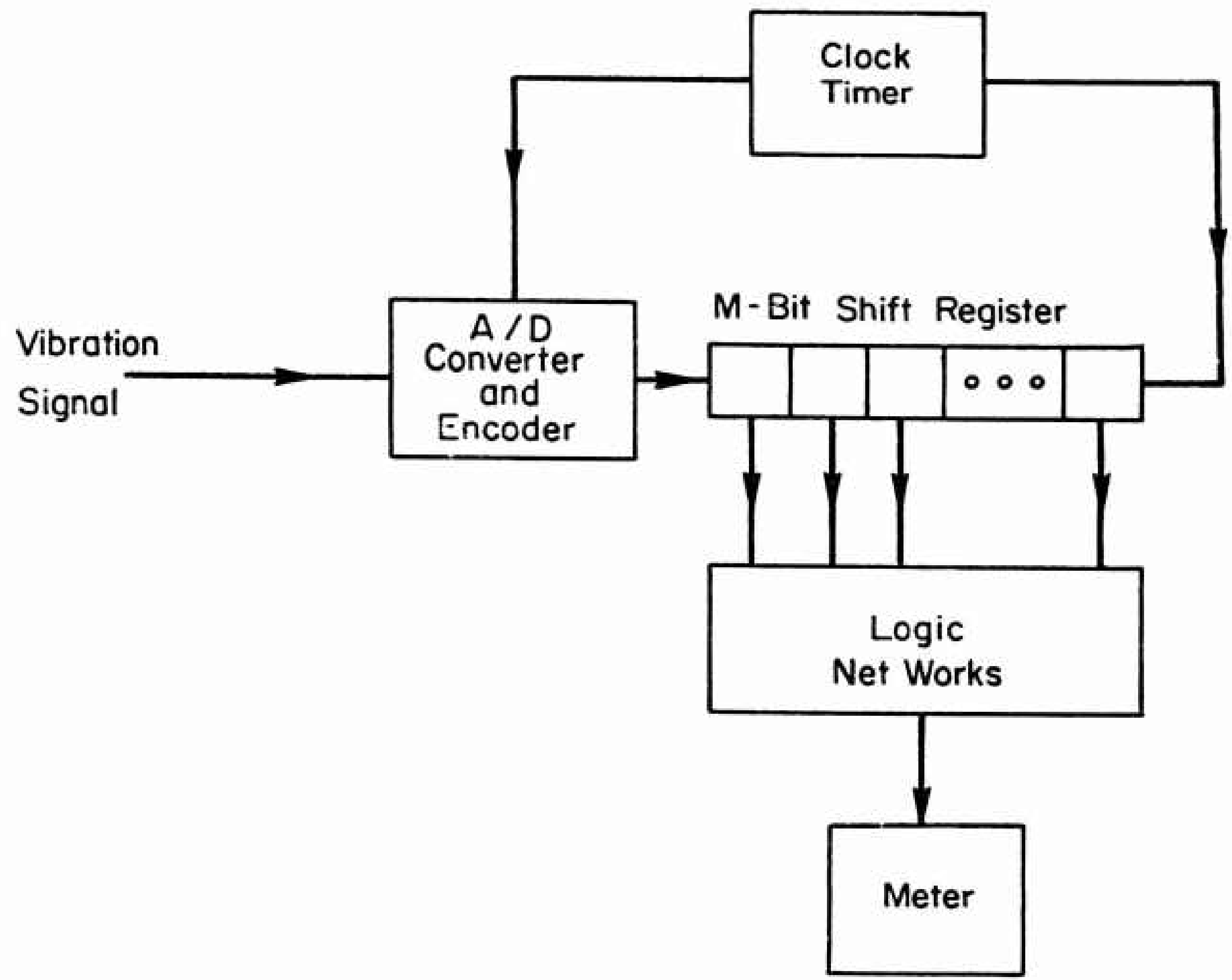


Figure 33. Block Diagram of FOBW Analysis Implementation.

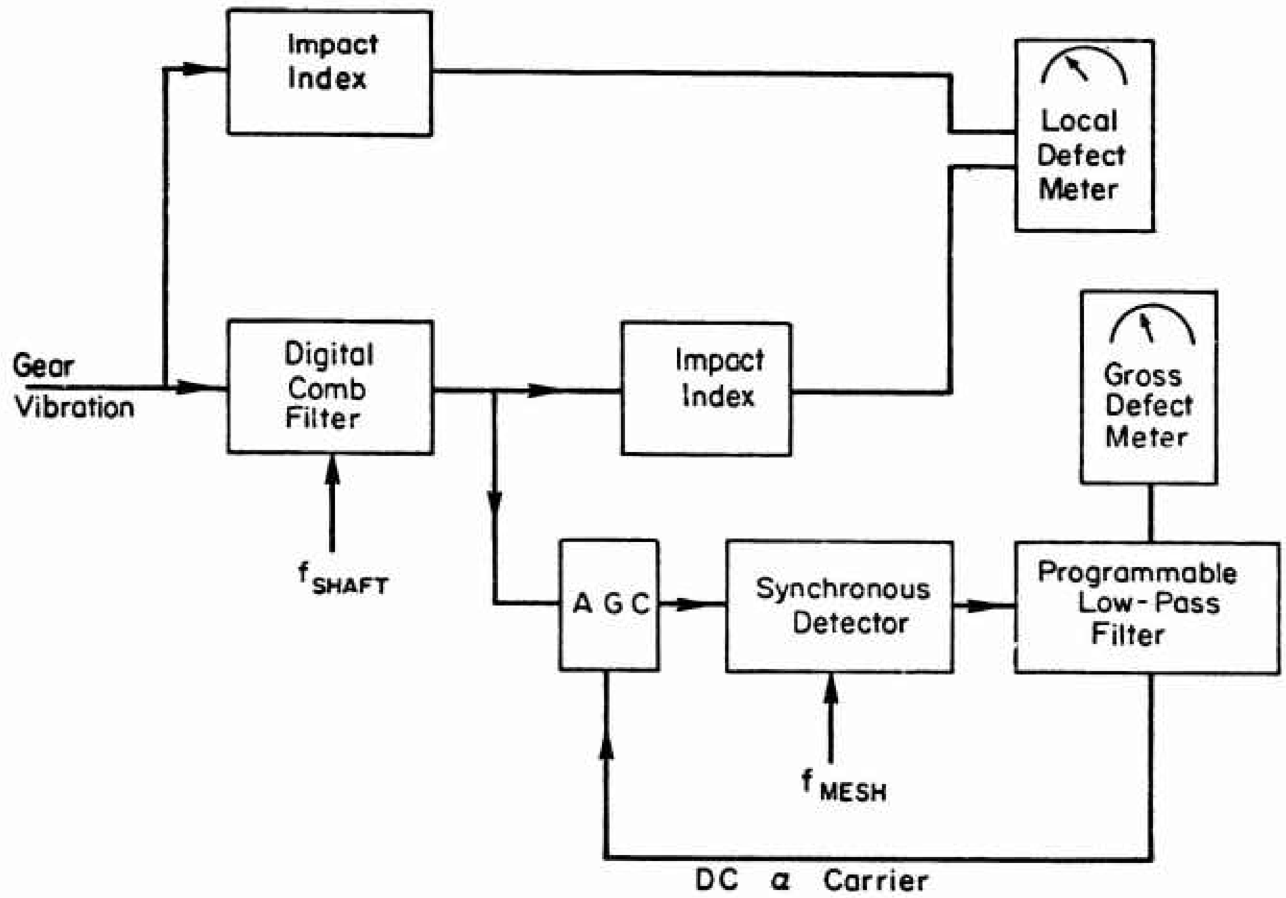


Figure 34. Block Diagram of Gear Analyzer.

The impact index analysis is performed in a manner quite similar to that performed for a bearing, the major difference being that the signal now comes from a transducer which is mounted in close proximity to the gear (this is still likely to be in close proximity to some bearings).

The ratio of the harmonic energy to the gear mesh energy is found through the use of a digital comb filter (DCF) which is tuned to the mesh frequency. Due to the characteristics of the DCF, all the energy at the harmonics will be passed through the filter. A band-pass filter may then be used at the mesh frequency, and a dividing network is used to produce the harmonic ratio. For a normal gear, the ratio should be slightly less than one, and the value will rise as the malfunction becomes more severe. Both the impact index and this harmonic ratio are used as indicators of discrete failures in the gear. Discrete failures occur on a small portion of the surface area of the gear tooth as distinguished from gross failures.

The ratio of total sideband energy to gear mesh frequency energy is used as an indication of a gross defect in the gear. The output of the DCF set at the shaft frequency is passed through an automatic gain control (AGC) to a synchronous detector set to the gear mesh frequency. This device has the effect of folding the signal about the gear mesh frequency and then translating the gear mesh frequency to zero, where it appears as a DC bias in the signal. This translation causes the modulation energy to appear at shaft frequency intervals. By using a low-pass filter on the output of the synchronous detector, a signal proportional to the carrier energy controls the automatic gain control. The signal which is finally measured is proportional to the ratio of total sideband energy to that of the mesh frequency carrier.

The results of the three discriminant analyzers are read on meters as values from 1-10. This output may be monitored manually or automatically. Trending is easily observed. Absolute values to be used as indicators have not been sufficiently studied.

These discriminants were developed on the basis of deviation from sinusoidal action. Testing, which was done for helicopters, shows the possibility of their use as an indicator of failures. However, the data base which was used was very small and was developed from test stand experiments rather than flight conditions. Testing is also being done in conjunction with the TF-34 analyzer. The number of implanted gearing failures has not been very large. Thus, the results at this time are not conclusive.

One problem associated with the analysis, particularly the use of the impact index, is extraneous signals. If the extraneous signals are large enough, the index may be meaningless. To overcome this difficulty, time averaging may be incorporated into the analysis. Accurate synchronization with speed signals is thus required. The effect of load variations is not known at the present time.

GEAR WEAR DISCRIMINANTS

This analysis procedure is used to monitor the amount of wear which has occurred on a gear. It was initially developed by the Electronics Laboratory of the General Electric Company and Mechanical Technology, Inc., in a joint program for the Office of Naval Research. Further developmental work on the technique has been carried out by the General Electric Research and Development Center.

The basic premise of this technique is that gear wear causes a deviation from pure sinusoidal action in gears. Because of this deviation, and accompanying modulations of the vibration signal, the spectral amplitudes related to harmonics of the gear mesh frequency should grow in amplitude as some function of the degree of wear experienced. The prime indicators used were the ratios of the second and third harmonic to the fundamental gear meshing frequency.

A piece of hardware was built to produce the desired discriminants. It consisted of three band-pass filters to find the spectral amplitudes of the three monitored frequencies and dividing networks to calculate the ratios. A phase-lock loop is used to set the center frequency of the filters, thus eliminating the effects of speed variations.

The operation of this device is quite straightforward. Periodically the ratios are read and plotted as a function of service time of the gear. As wear occurs, the ratios will tend to grow in amplitude. A level must be set at which replacement is required. This is, in part, up to the judgment of the operator based on trending and previous experience.

The technique was initially developed through the experimental evidence produced by the ONR project. Gears were lapped to simulate varying degrees of wear, and the ratios were found to be increasing. An analytical development by MTI showed that the third mesh frequency harmonic vibration amplitude should increase with increased levels of wear. This trend was verified experimentally, but the amplitude changes were not predicted with any degree of accuracy.[59,60]

A problem has been found when the overall system signal is great and gear signals get buried in it. In these cases, time averaging has been employed with some success.[61] Little difficulty is encountered with speed variation due to the phase-lock loop and the ratioing procedure appears to minimize problems due to varying loads.

GENERAL NARROW-BAND ANALYSIS

This discussion applies to a wide variety of diagnostic schemes performed by a large number of different companies. It has been applied as a condition-monitoring tool for many types of rotating machinery.

The technique is based on the fact that given spectral frequencies of a vibration signal may be related to the characteristic frequencies of

components of the machine being monitored. For example, a given bearing will exhibit its particular ball and race pass frequencies as shown in Figure 35. By observing the spectral amplitudes and their changes at these bearing frequencies, information relative to the condition of the bearing may be obtained.

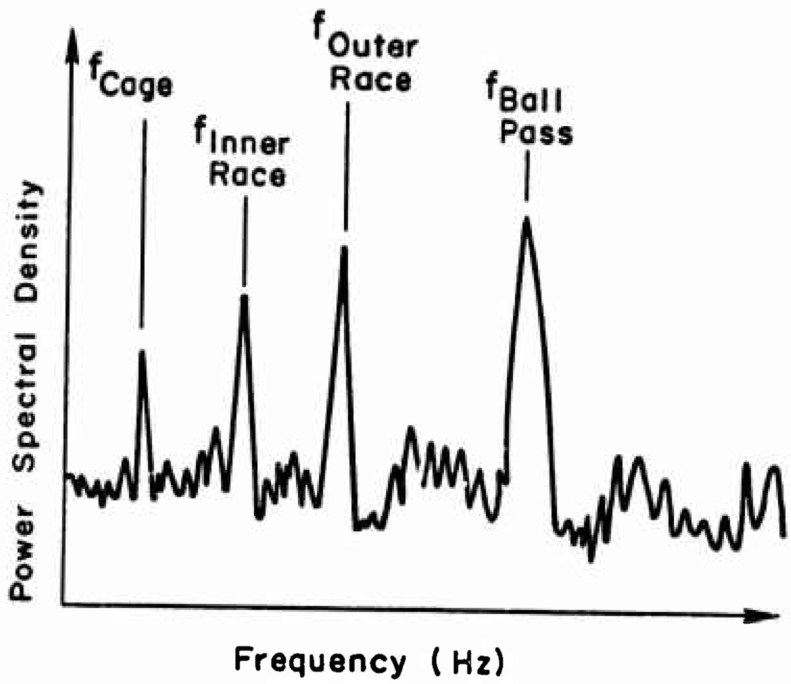


Figure 35. Typical Narrow-Band Spectrum for a Bearing.

In general, what is needed for the analysis is a vibration transducer, usually an accelerometer or velocity pickup, and a spectrum analyzer, e.g., bank of band-pass filters, swept frequency analyzer, real-time analyzer, or digital FFT processor. The amplitudes may be compared to some reference automatically, but they are most often compared manually by the operator. The operator must have some knowledge or skill related to the analysis of the frequency spectrum. Trending analyses may be performed on the amplitude characteristics, or absolute limits might be set, which could trigger the diagnosis of components as faulty.

Federal Scientific Corporation ran such an analysis with Avco-Lycoming, which will be considered as an example.[62] They used a Federal Scientific real-time analyzer and tracking adapter in a quality control operation. A bearing was mounted in a flywheel-driven test stand. A tracking adapter corrected the frequency analysis for speed variations and normalized the resulting spectrum. Faults on given parts of the bearing, i.e., inner race, outer race, or balls, were apparent due to the spectral amplitudes at the corresponding frequencies.

IRD Mechanalysis uses narrow-band analysis on various machines. Overall (RMS) levels are monitored until set levels are exceeded. At that time, a narrow-band analysis is done using a real time analyzer or tunable narrow-band analyzer, and the part which is causing high vibration levels is then determined from the spectrum.[63]

These are just two examples of uses of the narrow-band analysis. There are a wide variety of companies using various permutations of the technique with varying applications. The effectiveness of use ranges from very good to very poor depending upon the application. A critical part of the analysis concerns interpretation of the spectra. A large part of the success of such an analysis is usually attributable to the person doing this interpretation.

There are several difficulties associated with narrow-band analysis. There is a need for speed normalization. The frequencies of interest are nearly all functions of some input shaft speed. For this reason, monitoring must be done at the same operating speed each time or when possible; e.g., when digital sampling of the data is done, a tachometer signal should be used to normalize frequency. Another major problem occurs with unwanted signals in the analysis. The frequency ranges in which the components occur are such that many component frequencies appear in the same frequency region; e.g., harmonics overlap, broad sidebanding, structural resonances, etc. For this reason, it is often difficult to separate desired amplitudes from the rest of the vibration signal. This is particularly true of bearing component signals, which are often deeply buried in noise and other periodic signals. Another problem associated with this analysis is the effect of various loading conditions. Such changes can cause differences in spectral amplitudes without any change in component health. Thus, all monitoring must proceed under identical loading conditions.

HAMILTON STANDARD TEST-BED TECHNIQUE

This diagnostic procedure is a statistical pattern recognition technique developed for the UH-1H helicopter engine and power train. It was developed by the Hamilton Standard Division of United Aircraft Corporation for USAAVSCOM as part of the AIDAPS Test Bed Program.[64]

The goal of this program was to develop working hardware to be used in detecting faulty engine and power train components at the line-replaceable unit (KRU) level. The techniques were first developed on the basis of test stand runs in which both good LRU's and those containing implanted faults were tested. Further testing was later run on actual helicopters in the ground idle, hover, and flight operational modes. Finally, the last phase (E) of the project tested the techniques that had been developed on parts with condition unknown to the system designers. This testing was performed to measure the validity of the technique.

The following number of velocity and acceleration transducers were located on the engine and power train: engine - 3; transmission - 4; 90° gearbox - 2; 42° gearbox - 1.

These vibration signals were digitized and their power spectral density components were calculated via an FFT (Fast Fourier Transform) computing procedure. The frequency range of the analysis was 0-5000 Hz, and 341 frequency points (or bins as they were called in the Hamilton-Standard report) were calculated, giving an effective filter bandwidth of 14.6 Hz. The amplitudes corresponding to particular frequency bins were used as indicators in the analysis procedure. However, not all of the frequency bins were included in their final analysis. The following were considered: shaft rotational frequencies, all harmonics of shaft rotational frequencies, gear meshing frequencies, second harmonic of the gear meshing frequency, and first two upper and lower sidebands of gear meshing frequency. Amplitudes in all other frequency bins were discarded before applying the rest of the analysis.

As in all pattern recognition procedures, baseline characteristics are used in the analysis. Using data from ten to twelve "good" helicopter engines and power trains, arithmetic means and standard deviations of the PSD amplitudes were calculated for each of the frequency bins of interest and were used for baseline data. When compared with the signal produced from a helicopter of unknown condition, an amplitude in a given frequency bin was considered "bad" if it exceeded the "good" baseline mean amplitude by more than four standard deviations (4σ).

To rate the given frequency bins, a weighting scheme was developed. If a 4σ exceedance in a given frequency bin is unique, a weighting of 2 is given. If the frequency bin shows an exceedance in an interference band, a weighting of 1 is used. Weightings were also given with respect to the position of the given frequency bin. A weighting factor of 2 was used for the following: gear mesh frequencies, its first two upper and lower sidebands, shaft rotational frequencies, and the first two harmonics of shaft rotational frequencies. All other frequency bins of interest received a weighting of 1. As can be seen, weightings ranging from 1-4 could be given for frequency bins which showed greater than 4σ exceedances.

Once the weighting and 4σ exceedances were found, the procedure was relatively simple. The number of exceedances per LRU were counted, and if a given bin had a weighting of 2, it counted as two exceedances, and so forth. By experimental work, using LRU's known to contain failures, the following limits were set: engine - 7; transmission - 38; 90° gearbox - 8; 42° gearbox - 10. If the LRU showed a number of 4σ exceedances which was greater than this limit, it was judged to be faulty.

In the test bed program, the analysis was performed by mounting the transducers directly on the engine and power train. The vibration data was tape recorded in flight. (The final analysis used data from the hover mode of flight.) This taped data was then analyzed using a large digital computer; however, the hardware required could be assembled into a package which could be flown with the helicopter.

In the development of the analysis, an operator was required to take the data; this would not be required with an entirely on-board system. The

results are produced in terms of a "good" or "bad" LRU with a listing of 4σ exceedances.

After the technique was developed, a testing phase (Phase E) of the program was run. On the basis of eight flights or a total of 32 possibilities (8 flights times 4 LRU's), the technique produced a 90% accuracy. The eight flights did not include any faulty gearing.

The testing does not require a constant level of engine speed. In the digitization process, a tachometer reference signal controlled sampling rates to negate any frequency shifts caused by speed fluctuations. Load fluctuations did cause difficulty, as it was found that the technique developed from data of one flight mode could not be used successfully on another mode. Initially, test stand data was intended to be used for baseline information, but, because of variations in loading, this was found to be impractical.

BEARING "RING" ANALYZER

This diagnostic technique uses a structural ringing of a bearing which is caused by an internal fault as the indicator of bearing condition. It has been developed and prototype systems have been built by Mechanical Technology, Incorporated (MTI).

When a bearing exhibits a discrete fault, e.g., scratch, pit, or spall, an impact is produced every time the fault passes through a ball-race interface. By experimental work, it was found that this impact can excite what is believed to be a high-frequency resonance of the mounted bearing. It appears that the frequency excited is a higher order race resonance, but an absolute determination has not yet been made. By monitoring the spectral amplitude of the resonant "ring" and observing its forcing function, a determination of bearing condition is made.[65]

A piece of hardware has been built to perform this analysis. Figure 36 shows a block diagram of its operation. The initial step in implementation is a determination of the characteristic frequency at which a particular bearing will ring. This may be done experimentally by scribing the bearing, running it, and monitoring the spectra. Presently, a completely analytic prediction procedure is not available. Once the frequency is determined, the vibration signal from that type of bearing is passed through a band-pass filter with the center frequency set at the "ring" frequency. The output of this signal is then envelope detected. If the amplitude of the envelope is significant, a defect is said to exist.

The next step determines the position of the defect. The filtered and envelope-detected signal is passed through three more band-pass filter circuits: one for the inner race-pass frequency, one for the outer race-pass frequency, and one for the ball-pass frequency. The output from these circuits is monitored. If only the "ring" frequency filter shows significant levels, a general wear or surface degradation is diagnosed. If one

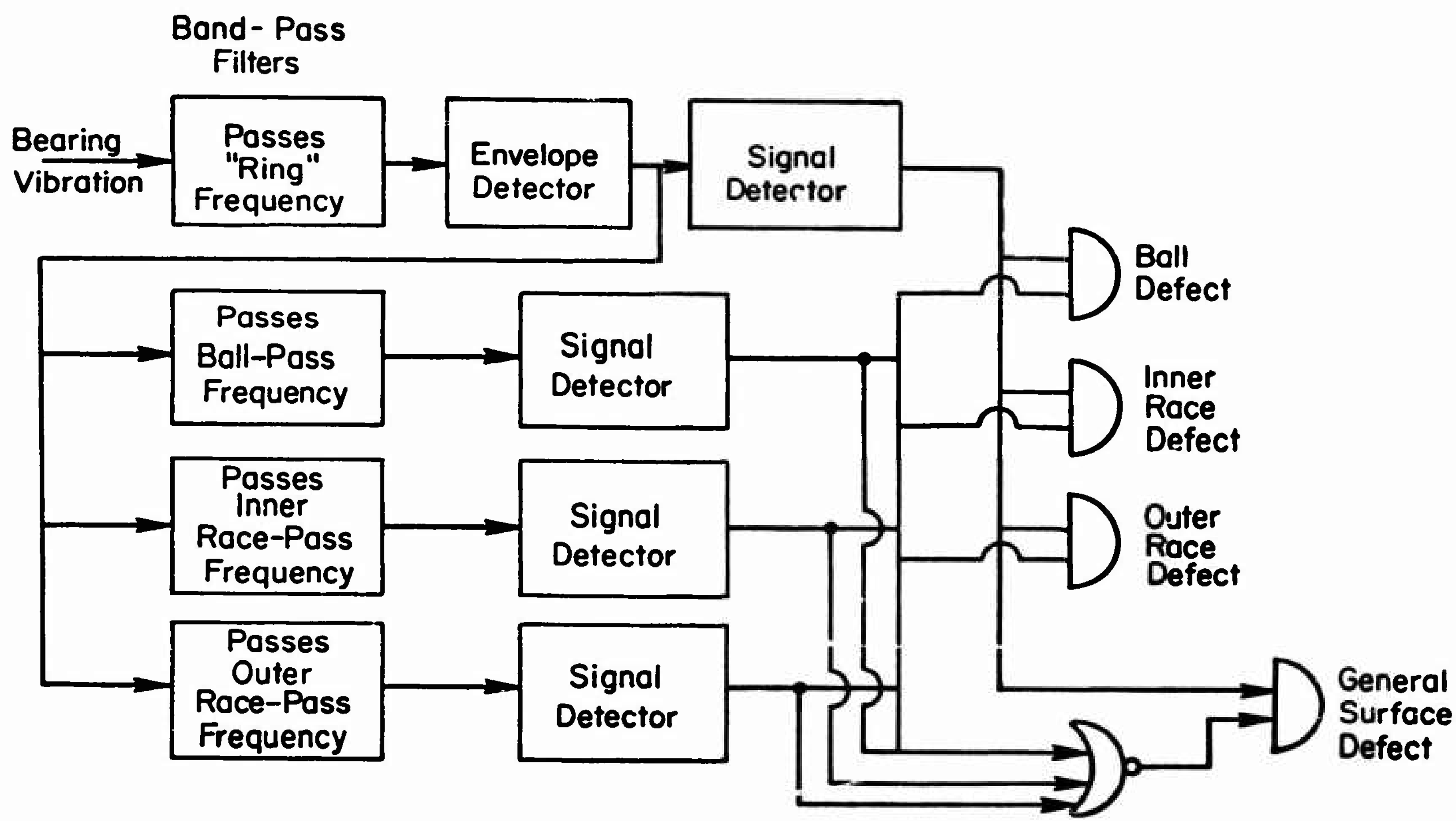


Figure 36. Block Diagram of MTI High-Frequency Bearing Analyzer.

of the other filters shows significant amplitude levels, the fault is diagnosed as discrete and occurring in the respective bearing member. Once the frequency of the "ring" is determined, discrete triggering levels may be used, thus automating the analysis. The procedure requires one accelerometer per bearing and diagnoses each bearing individually. Due to the preprocessing before the envelope detection, amplitude calibration is not possible. Thus, it is not possible to determine whether one bearing is worse than another on any absolute scale--only that it has a fault.

The technique was initially developed during a quality control program for use on gyro bearings by NASA at the Marshall Space Flight Center.[66] Further quality control application studies have continued as well as in-house studies at MTI. The testing has been quite successful on quality control type tests, i.e., run on a test stand. No significant amount of testing has been done to determine the effectiveness of the procedures when the bearing is a part of a large, complicated structure.

One strong point of this procedure concerns the frequency ranges of the analysis. In the data taken, the "ring" occurred above 20 kHz. Since there are not many other spectral components in this frequency range, the signal is easy to discern. The resonance, being a structural characteristic, is not speed dependent. If only the indication of a fault is desired, i.e., the specific position (race, ball, etc.) is not desired, testing can occur at any operating speed. From experimental evidence, load variations do not appear to have a significant effect on the signal.

Some analysis of the high-frequency components in the spectra of bearings has been performed by a number of investigators.[67,68,69] However, none of these investigators have developed the analysis procedure much beyond simply looking at the spectra.

TEST-BED RATIO TECHNIQUE

This diagnostic procedure is a pattern recognition technique developed for use on the UH-1H helicopter engine and power train. It was developed by the Northrop Corporation Electronics Division for USAAVSCOM during the UH-1H AIDAPS Test Bed Program and was performed as a parallel study to the study done by Hamilton-Standard.

A simple procedure was developed. Power spectral density plots of the output from an accelerometer mounted on one of the LRU's of the drive system, i.e., engine, main transmission, 42° gearbox, or 90° gearbox, were prepared for a number of "good" systems as well as for a number of systems containing faulty parts. It was observed that in some frequency bands, peak amplitudes rose when faulty parts were installed, while in others the amplitudes fell. These observations were made by manually scanning the data. Ratios of the peak amplitudes in these bands were used as indicators of the system condition. Figure 37 shows a sketch of this type of occurrence. In Figure 37(a), where all components are "good", the ratio of peak amplitude in band X to that in band Y is

$$\frac{X}{Y} = \frac{1}{1.5} = 0.667 \tag{63}$$

In Figure 37(b), where the system has a faulty component, the ratio is

$$\frac{X}{Y} = \frac{3.2}{1.0} = 3.2 \tag{64}$$

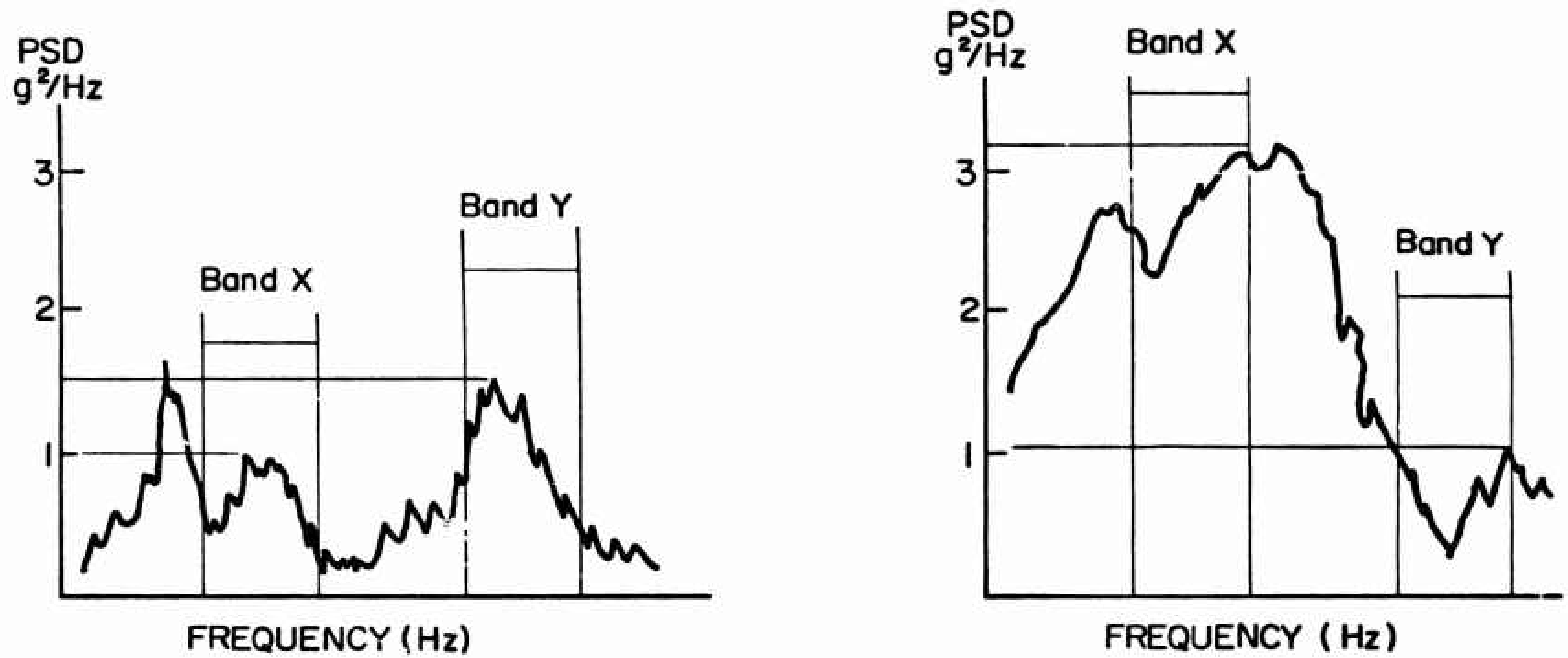
If a limit is set at 2.0 for the ratio of a good part, the fault would be diagnosed. Table II shows the ratio and threshold limits finally selected for the test bed program. It should be noted that this procedure was developed specifically for the UH-1H helicopter with a given set of failure modes.

TABLE II. RATIO AND THRESHOLD LIMITS

Component	Ratio	Threshold	Lower Band (Hz)	Upper Band (Hz)
Engine	B/A	1.0	(A) 605-695	(B) 755-875
	F/D	4.5	(D) 1670-1890	(F) 2340-2660
	G/F	1.0	(F) 2340-2660	(G) 4000-4200
42° Gearbox	M/L	1.0	(L) 2400-2700	(M) 4600-5000
	J/K	2.0	(K) 1400-1700	(J) 1300-1400
Transmission	Q/P	1.0	(P) 800-1000	(Q) 3300-3600
90° Gearbox	θ/β	10	(β) 1535-1581	(θ) 2046-2139
	η/β	4	(β) 1535-1581	(η) 3023-3162
	θ/α	0.5	(α) 140-456	(θ) 2046-2139
	η/α	0.25	(α) 140-456	(η) 3023-3162

Once the ratios are determined, the mechanization of the system is quite straightforward. Heterodyne tracking filters are used to sweep through the frequency ranges of interest. Peak-hold networks pick off the peak amplitudes in each range, and divide networks produce the ratios. The system implementation uses only one transducer per LRU; it was found that the technique could be used for either flight or hover mode operation, but the same ratios could not be used for both test stand and flight modes. The operation of this system will be completely automatic. When the threshold limits are exceeded, alarms will be triggered.

The testing and development of this technique were entirely associated with the AIDAPS Test Bed Program. In Phase E (the testing phase of the program



$$\frac{|X|_{peak}}{|Y|_{peak}} = \frac{1}{1.5} = 0.667 \qquad \frac{|X|_{peak}}{|Y|_{peak}} = \frac{3.2}{1.0} = 3.2$$

Figure 37. Test-Bed Ratio Data for Good and Bad Systems.

with severely degraded parts), the technique produced an 86% effectiveness on the main transmission, 42° gearbox, and 90° gearbox.[70]

The use of ratios generally provides some normalization factor. In the testing of this technique, the ratios tended to negate the effects of both system noise and the varying load on the helicopter. Speed variations will cause difficulty by shifting the frequency bands. Thus, the bands are selected for one flight mode, and all analysis must be done in that mode. Because of the broad bandwidth of the frequency bands, small variations in shaft speeds should not present much difficulty.

An extension of this analysis procedure was attempted in a second technique, the spectral vector. In the spectral vector analysis, a number of frequency windows in the spectrum were used to form a family of ratios, rather than the single ratio employed in the procedure discussed. Since only a small amount of work was completed with the spectral vector, the results were inconclusive.

OPTIMUM-SEEKING CLASSIFIER

This pattern recognition analysis procedure is the basis of a diagnostic program proposed by Scope Electronics, Inc., for use in diagnosing the condition of helicopter power trains.[71]

This diagnostic system uses acceleration or microphone signals from the LRU's being monitored. Once the signals have been preprocessed to decrease noise problems, spectral components are found via an FFT analysis. Markel filtering, which would help resolve some of the frequency jitter problems, was presented as a possible preprocessing technique. After the calculation, the spectral components are used as the features in the classification routine.

As in all pattern recognition techniques, this one requires data from "good" helicopters and those helicopters containing faults, to prepare "good" and "bad" statistical baselines. Once this baseline data is available, the classifier routine will determine which features show the greatest distinction between "good" and "bad". This technique arranges the n-features for each spectrum into an n-dimensional vector for each helicopter condition. The classifier then determines the surface in n-space which best separates "good" from "bad". The results are presented as an ordering of features and are based on the highest probability of successful classification using that number of features.

Once the classifier has been applied to the baseline data and the ordering is finished, a decision as to the probability of success that is desired must be made. Subsequently, the number of features required for success will be determined, and hardware, in the form of some sort of special-purpose filtering, will be built to measure these features. Acceptable limits must then be set for these features. Logic circuitry will be built to provide results as to whether or not a system is in "good" condition. These results may be presented in whatever form is desired.

A sample of data taken during the AIDAPS Test Bed Program was analyzed by this method (see page 120 and Appendix V).

The preprocessing of the data is expected to minimize unwanted noise problems. Speed variations, however, will probably need careful monitoring because of the strong dependency of characteristic frequencies on speed. The effect of load variations is not known because no testing was done.

SHOCK PULSE ANALYZER

The shock pulse technique is directly applicable to the detection of faulty rolling-element bearings. The technique and instrumentation were developed by AB SKF, Gotherburg, Sweden, and are marketed in the United States by SKF Industries Inc. The shock pulse meter is a self-contained package which is purported to have the ability to detect faulty bearings. It has been marketed extensively in Europe, with the predominant users being members of the petrochemical, paper, and steel industries.

When a bearing race or rolling element contains a discrete fault, such as a pit or spall, the rolling contact between this fault and the other rolling elements will result in repetitive impacts of very short duration. These impacts excite structural resonances. Another phenomenon which results from these impacts is the propagation of a stress wave through the structure. This stress wave, called a shock wave by SKF, is emitted in the direction of the force of the impact, and it travels at the speed of sound through the material. The length of the pulse is equal to the time duration of the impact force. As the wave travels through the part, its energy dissipates through the structure, thus reducing the wave pulse amplitude and lengthening its time duration. The only case of stress wave propagation which has been extensively studied in the literature is the propagation of stresses in longitudinal bars.

The shock pulse technique utilizes an accelerometer which ideally is placed very close to the subject bearing. The shock pulse travels through the bearing and creates a pulse displacement input to the accelerometer. This pulse is of short enough duration that it excites the free resonance of the accelerometer (approximately 39 kHz in SKF's system). This excitation will occur only if the shock pulse duration is less than one-fourth of the period of the free vibration of the accelerometer (6 μsec in this case).

A simplified block diagram of the shock pulse meter is shown in Figure 38. The output of the accelerometer is passed through a high-gain amplifier tuned at the resonant frequency of the accelerometer. This amplifier acts as a very sharp band-pass filter. The signal is rectified, averaged, and passed through a peak-sample-and-hold network which quantizes the information. The output is displayed on a counter which provides the frequency of peaks above any desired peak amplitude. Signal RMS values may also be displayed.

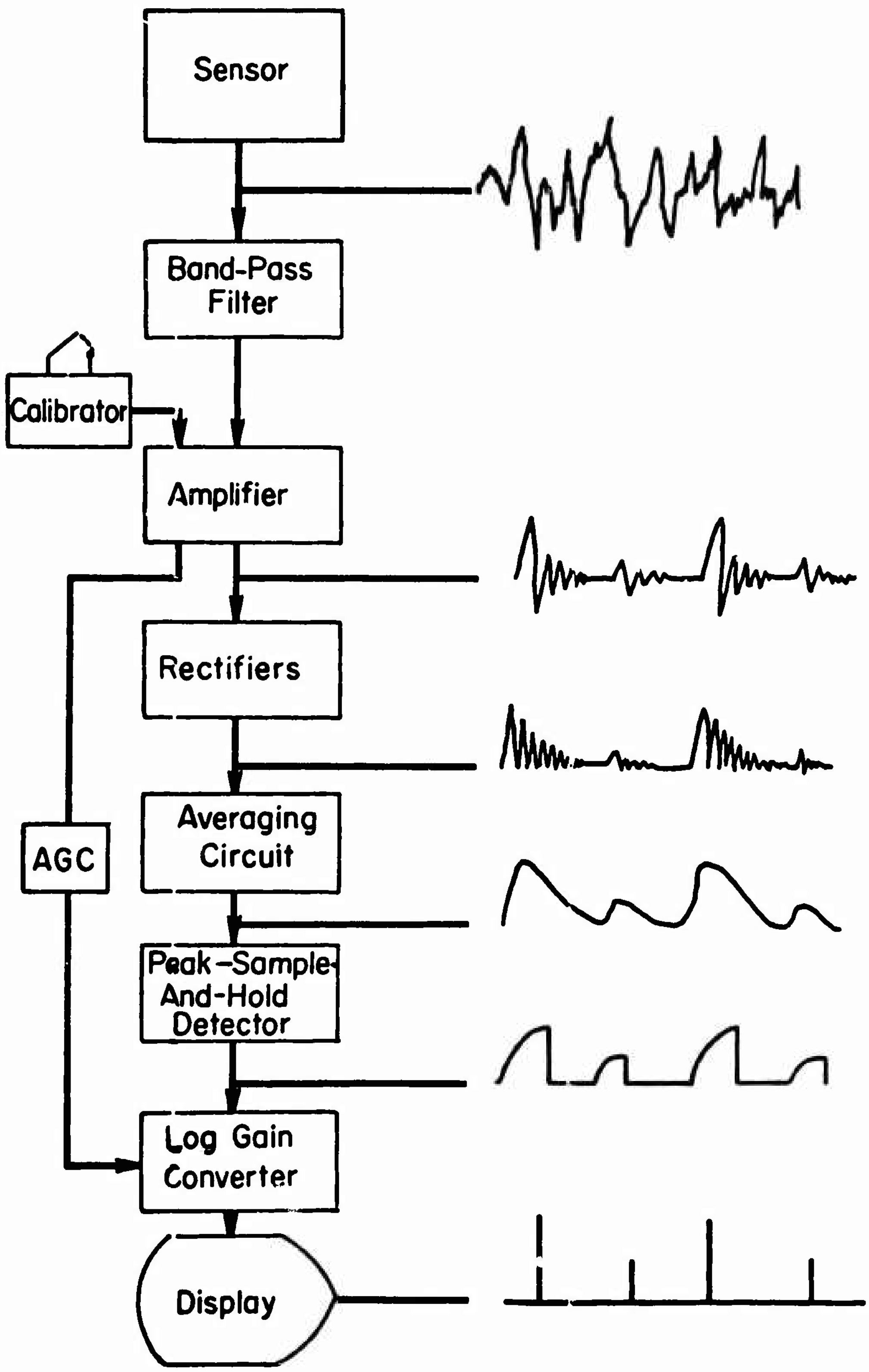


Figure 38. Block Diagram of Shock Pulse Meter.

The frequency of occurrence values may be used to provide an amplitude histogram of the output (event per unit time) vs. amplitude. It has been found (through experience) that the shape of this curve is an indicator of bearing health. If the curve is flat in the high-amplitude range, i.e., a higher frequency of high-amplitude peaks, the bearing is in poor condition since a good bearing shows a more or less linear curve. These two curves are shown in Figure 39. Thus, by monitoring the change in this curve, the condition of the bearing can be followed since the change in curve shape is gradual as bearing degradation occurs.

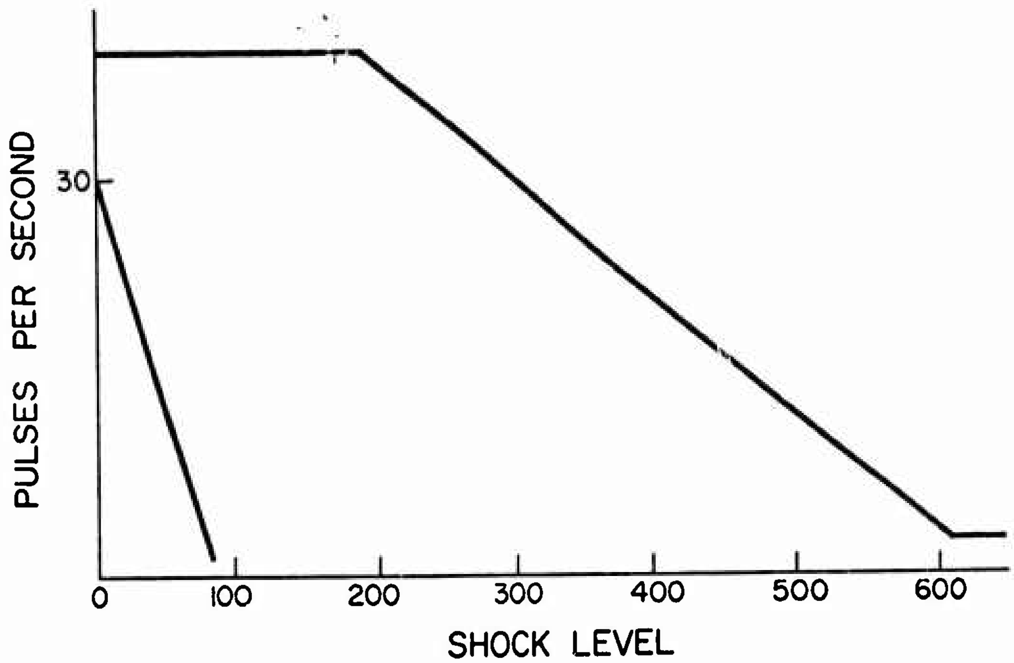


Figure 39. Typical Shock Pulse Output.

A special accelerometer mounting stud and fixture are used to guarantee repetitive mounting. The stud is tapped permanently into the machine structure. It is a simple, but unique, operation to connect the accelerometer to this stud.

The amplitude signals which are received from the unit are a logarithmic value of the input amplitude. The value is strongly dependent on bearing speed. Therefore, the measurements must always be taken at the same shaft speed. An amplitude normalization is apparently not available for two major reasons. The chief reason is the strong speed sensitivity. All bearings in a power-train are not running at the same speed. It is possible that some type of speed calibration could be developed, but to date this has not been done. A second reason is that considerable amplitude attenuation is caused by the passage of the shock wave across each interface. SKF estimates an average of 14 dB loss per interface.

Consequently, the signal from the same bearing could show a significant difference depending on whether the fault occurs on the inner or outer race. Because of these problems, it appears that the bearings must be analyzed individually. Predictions of degradation must come from qualitative observations of a plot of each individual bearing location.[72]

Because of the interface problem, there is some question regarding the number of transducers which are needed on a single transmission containing many bearings. In an ideal application of this technique, it would be desirable to have one accelerometer stud located as closely as possible to each bearing.

SUMMARY

Table III was prepared as a summary of this section. This table shows the major characteristics of the specific techniques described in an easily viewed format. The table is prepared in the following form:

Technique: corresponds to the specific technique.

Component: describes component of system to be analyzed, i.e., gear, bearing, other, or all.

Transducer: type of transducer used, whether vibratic pickup or acoustic pickup.

Processing: describes whether processing is to be performed via analog or digital hardware.

Baseline: describes whether baseline data is required and, if so, whether good baselines, bad baselines, or both are needed.

Output: describes whether an automatic output is available or whether a manual (operator performed) analysis is required.

Normalization: describes whether normalization on load, speed, or noise characteristics is performed.

Testing: describes whether technique has been tested in the lab (experimental tests under controlled conditions) or in the field (on actual operating machinery).

X's are used to indicate the efficacy of the given comment.

TABLE III. SPECIFIC DIAGNOSTIC TECHNIQUES																
	Component			Transducer		Processing		Baseline		Output		Normalization			Testing	
Technique	Gears	Bearing	Others	Vibration	Acoustic	Digital	Analog	Good	Bad	Manual	Automatic	Speed	Load	Noise	Lab	Field
Curtiss-Wright Sonic Analyzer	X	X	X		X		X	X			X	X			X	X
Noise-Corrected Spectrum Energy	X				X		X	X		X		X		X	X	
Correlation Analysis	X	X		X	X	X		X	X		X	X		X		
Composite Exceedance	X	X		X	X	X		X	X		X					
Likelihood Analysis	X	X		X	X	X		X	X		X				X	
Bearing Impact Index		X		X			X				X		X		X	X
FOBW (G.E.)	X	X		X	X	X		X	X		X				X	
Gear Discriminant	X			X			X	X			X	X			X	
Gear Wear Discriminant	X			X			X	X		X		X			X	X
General Narrow-Band	X	X	X	X	X	X	X	X		X		X			X	X
Ham-Std Test Bed	X	X	X	X		X		X	X		X	X			X	X
Bearing "Ring"		X		X			X	X			X			X	X	
Northrop Test Bed	X	X	X	X			X	X	X		X	X	X		X	X
Optimum-Seeking Classifier	X	X	X	X	X	X		X	X		X	X	X		X	
Shock Pulse		X		X			X	X		X					X	X

EVALUATION OF TECHNIQUES

This section will present the analyses of data that were performed by OSU in an effort to evaluate the various diagnostic techniques and methods of signal analysis. Several approaches to vibration data analysis were taken:

1. Analysis of available AIDAPS Test Bed Program helicopter data.

2. Study of signal analysis techniques for bearing diagnostics using a small test rig.

3. Development and evaluation of a relatively simple mathematical model of a bearing for use in fault detection evaluation.

4. Stress wave analysis.

The results of the above approaches will be given after a brief presentation of the form of typical helicopter vibration data to allow the reader to become familiar with the nature of helicopter vibrations.

HELICOPTER COMPONENTS

Typical helicopter power trains fall into two classes: the single-engine helicopter such as the UH-1, and a twin-engine, twin-rotor vehicle such as the CH-47.

In the single-engine helicopter, the engine power is transmitted through a main transmission which consists of a spiral bevel gear input and a double reduction planetary gear train to the main rotor. Tail rotor power is also channeled through a gear reduction in the main transmission and then along a shaft to the rear of the helicopter, where the power is transmitted through two gearboxes to the tail rotor. In the UH-1, these two gearboxes are termed the 42° and the 90° gearbox, respectively.

In the twin-engine, twin-rotor helicopter, power from the two engines is combined in a mixing transmission which has shafting going to separate planetary transmissions for the fore and aft main rotors.

Since most helicopter data has been gathered for the UH-1 type transmission, discussion will be primarily centered around the UH-1 configuration and hardware.

AVAILABLE HELICOPTER DATA

One purpose of this study was to investigate sources of helicopter data suitable for diagnostic studies. This data would have to contain an adequate number of tests with known faulty parts as well as good baseline runs. Several sources of such data were uncovered.

Perhaps the most extensive testing of helicopter power trains containing faults was performed in the AIDAPS Test Bed Program sponsored by USAAVSCOM. Data was gathered by two vendors (Hamilton-Standard and Northrop Corp.) from UH-1 helicopter transmission in both a test stand and actual flight modes of operation.

Test stand runs were performed on individual LRU's, i.e., the main transmission and the 90° and 42° gearboxes were tested separately. Many implantations of faulty gears and bearings were used in test runs in addition to the test runs of good parts. In the flight modes, approximately twelve good part baseline tests were made. Faulty part tests were not as extensive as in the test stand studies and did not contain any faulty gears. The data taken by Hamilton-Standard was made available to OSU by USAAVSCOM for analysis in this program. This data was limited to the 0-5 kHz frequency range.

Acoustic data on helicopters has been gathered by Curtiss-Wright and the Eustis Directorate of USAAMRDL. This data was taken from two microphone positions in UH-1 helicopters. It contains "good" baseline data and data from helicopters scheduled for overhaul for which faulty parts were discovered. Other data, which is of a quality to be used for diagnostic studies, was taken by Boeing-Vertol for the Naval Air Propulsion Test Center, Trenton, N. J. Under the Boeing study, a CH-47 forward transmission was placed in a test stand and operated with the following implanted faults: spalled roller bearings, spalled first-stage sun gear, excessive axial play of pinion gear, and insufficient spiral bevel gear bolt torque. This data, which had a frequency bandwidth from 0-20 kHz, was subsequently analyzed by Boeing-Vertol and General Electric Avionics Division. It is on analog tapes and is presently held by G.E. Avionics Division and the Navy.

Other vibration data on helicopters besides those mentioned has been taken. The description of the data here was provided because the information concerning it was readily available to this study.

TYPICAL HELICOPTER DATA

In an effort to identify specific data characteristics peculiar to helicopters and their transmissions, a portion of the Hamilton-Standard UH-1 AIDAPS data was obtained for analysis. Particular emphasis was placed on the hover and high-speed level-flight data, as these were the flight modes which were chosen by both Hamilton-Standard and Northrop for diagnostic purposes.

Five transducer locations were used in the OSU analysis and shall, hereafter, be referred to with Hamilton-Standard's parameter notation:

Parameter 61: Accelerometer located at 42° gearbox output quill.

Parameter 64: Velocity pickup located at 90° gearbox input quill.

Parameter 123: Velocity pickup located on main transmissions at the upper mast shaft.

Parameter 125: Accelerometer located at the input quill of the main transmission.

Parameter 126: Accelerometer located at the tail rotor output of the main transmission.

Time Plots

Typical time data for parameters 61, 123, 125 and 126 are shown in Figure 40. It should be noted that most of the data has a characteristic frequency which tends to overshadow all other frequencies. In the case of parameter 61 on the 42° gearbox, a low-frequency component at approximately 100 Hz is superimposed on the higher frequency components. The frequency superimposed on parameter 123 data is approximately 30 Hz, which is close to three times the rotor blade-pass frequency. The higher frequency data is composed predominantly of gear mesh frequencies and harmonics.

Frequency Spectra

The frequency spectra shown in Figures 41 through 44 for the five transducers bear out the fact that the highest amplitude components of the data are at the gear mesh frequencies. Frequencies calculated for a UH-1 helicopter operating at 6600 rpm are shown in Appendix IV. A higher resolution plot (Fig. 41) to 500 Hz was made for parameter 61 in an effort to identify the bearing frequencies. This spectrum represents a bearing having an outer race fault whose computed frequency is 325 Hz. Whether the frequency peak at 325 Hz is the twelfth harmonic of the 90° gearbox shaft frequency or the bearing frequency is subject to conjecture since both are computed to be the same frequency. It should also be noted that the 90° gearbox output shaft frequency and its harmonics are very apparent in the 42° gearbox spectrum and that the even shaft harmonics are greater than the odd harmonics. These even harmonics correspond to the harmonics of the tail rotor blade-pass frequency. In the 0-5000 Hz plot of parameter 61, many multiples of the 42° gearbox shaft frequency appear. Also, sidebands about the gear mesh are very apparent.

Figure 42 shows that the velocity pickup used for parameter 64 is not as sensitive to the higher frequency vibrations as it is to the lower frequencies.

Probability Density Functions (PDF)

Typical probability density functions for "good" helicopter data are shown

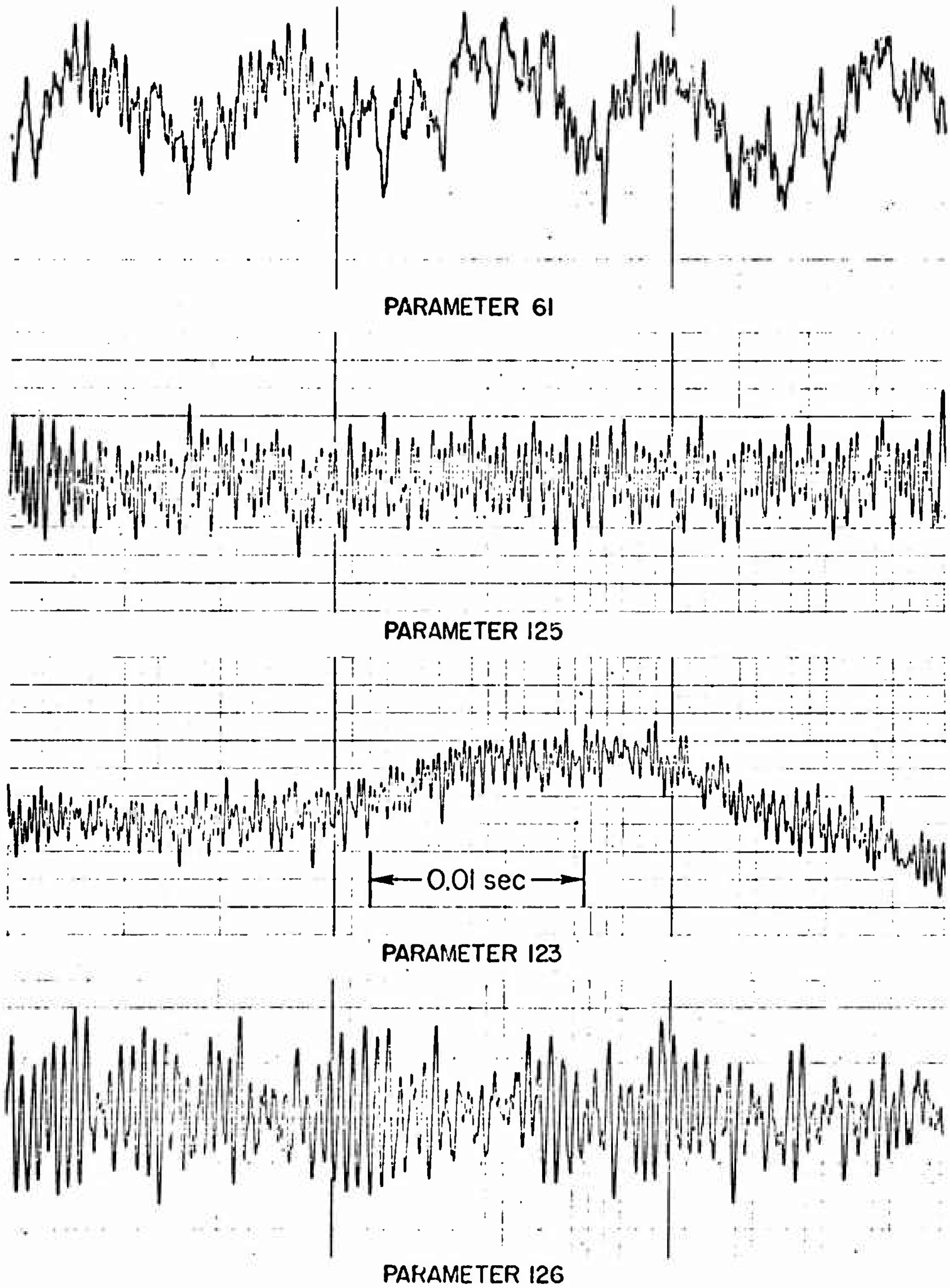


Figure 40. Typical Time Plots of AIDAPS Test Bed Data.

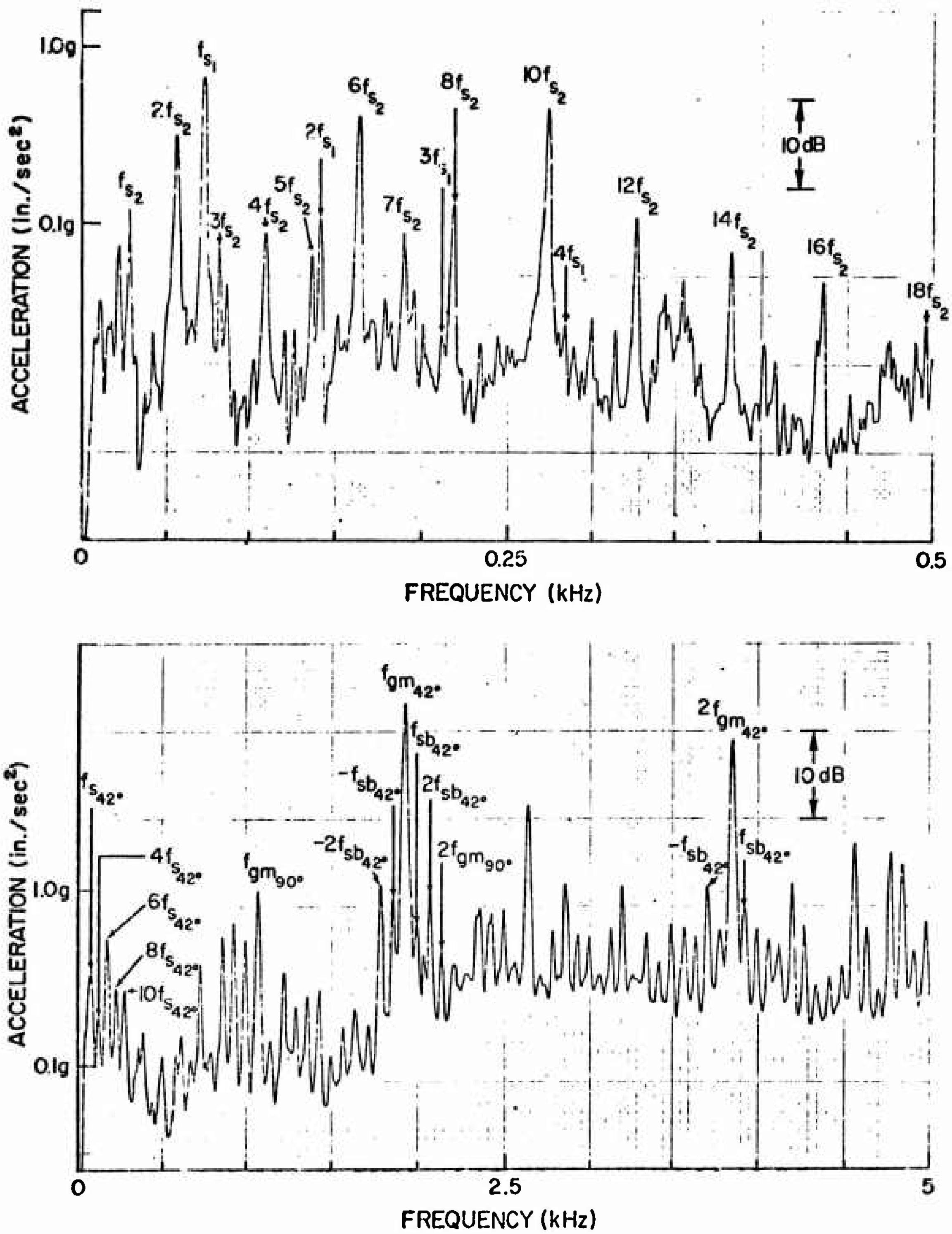


Figure 41. Spectra for Parameter 61.

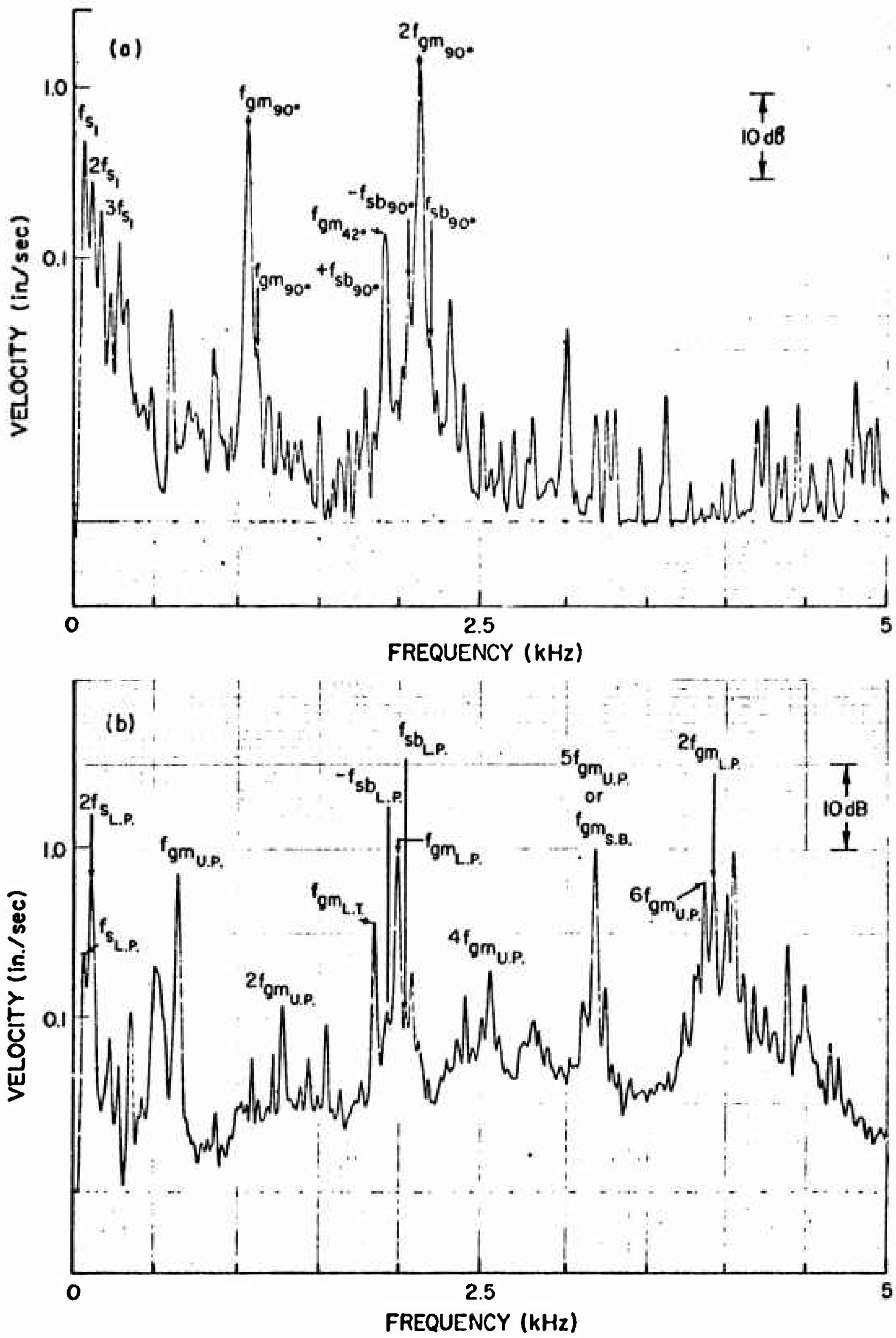


Figure 42. Spectra for Parameter 64.

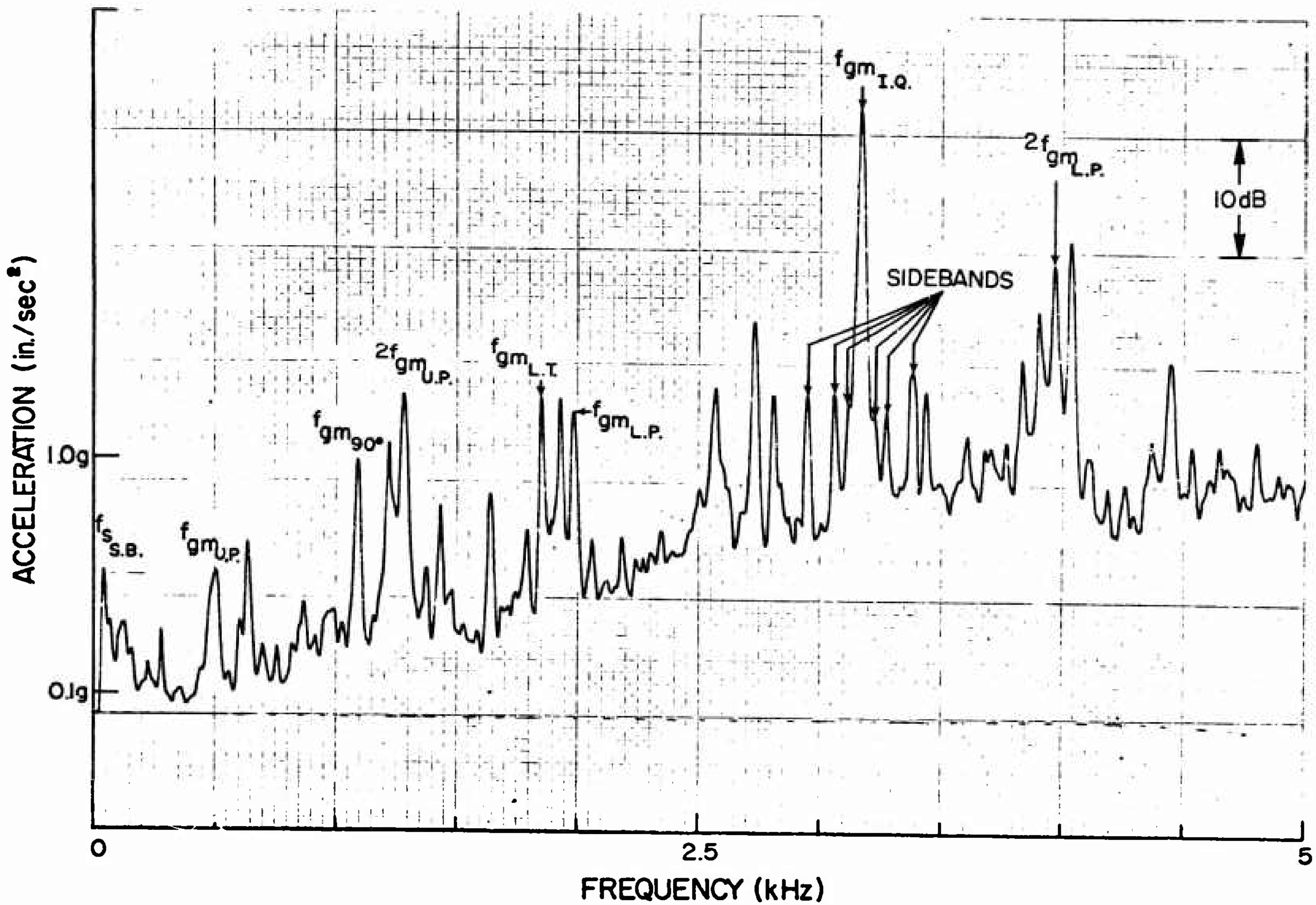


Figure 43. Spectrum for Parameter 125.

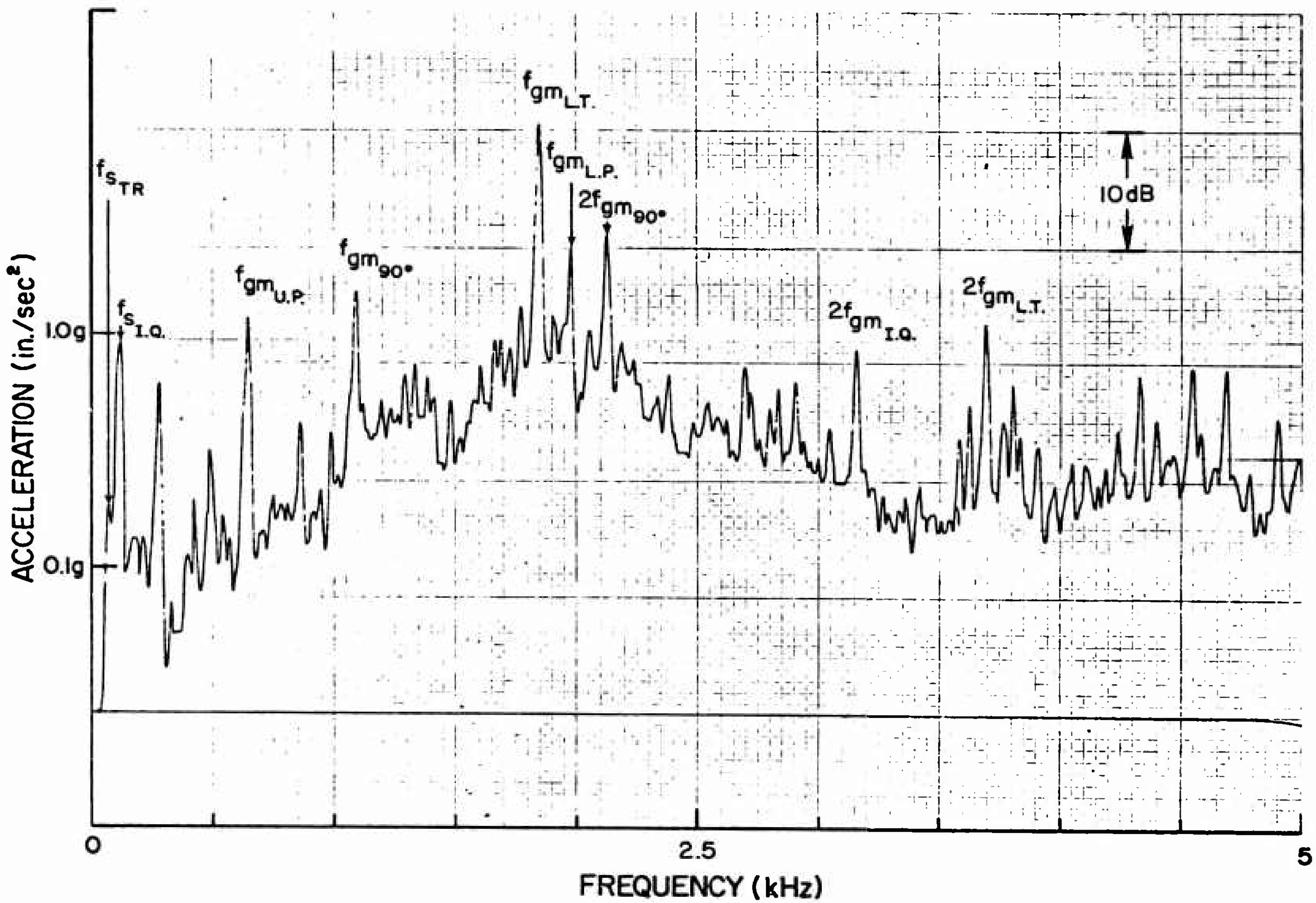


Figure 44. Spectrum for Parameter 126.

in Figures 45 and 46. In Figure 45 (parameter 61), probability density functions for two separate runs are shown. The differences in the probability density function slopes are quite evident. Both runs had good parts near the transducers. However, there was a bad main mast bearing in the second run which may have had some effect on the data. Figure 46 shows data for parameter 126 from two runs: the first with all good parts, the second with a faulty tail rotor bearing (located very near transducer 126). Again, a difference in the shape of the curve is noted; the good bearing has a Gaussian shape, while the data with a faulty component yields a flatter shaped curve which might indicate more strongly sinusoidal vibration.

The probability density functions for other test runs were of a similar nature to the ones shown.

Correlation Functions

Autocorrelation functions having 100 time lags were plotted for each of the subject parameters. Samples of these plots are shown in Figures 47 and 48. All of the autocorrelation functions indicate very little randomness and a high degree of repetitiveness in the signals. This verifies observations from the time plots and the frequency analysis.

Figure 47 depicts autocorrelation functions from two different runs for parameter 61. The fundamental time lag of the first plot is the inverse of the 42° gearbox mesh frequency. Both of the plots of Figure 47 are for the same time lag, but significant differences in shape are observed. Figure 48 shows data for parameter 126.

The two plots show a lag of 0.35 msec, which corresponds to the spiral bevel gear mesh frequency. For this parameter, the correlation function shapes varied from run to run.

DATA VARIATIONS

Several topics related to data gathering will be discussed in this section; these topics include the number of transducers necessary, the operational mode in which data should be taken, the day-to-day statistical variations in data from one helicopter, and the variations from one helicopter to another.

In selecting transducer locations, it would seem that the smaller the number of transducers, the better. However, in any mechanism as complex as the main transmission of a helicopter, it is doubtful whether one transducer could adequately identify failures at all locations. The three transducer locations (input quill, upper mast, and tail rotor) seem to yield extensive information on the components nearest to their location without too much overlap. Whether these transducers are adequate for monitoring other internal parts would be pure conjecture at this time and would certainly depend upon the discriminant being used. The 90° and 42°

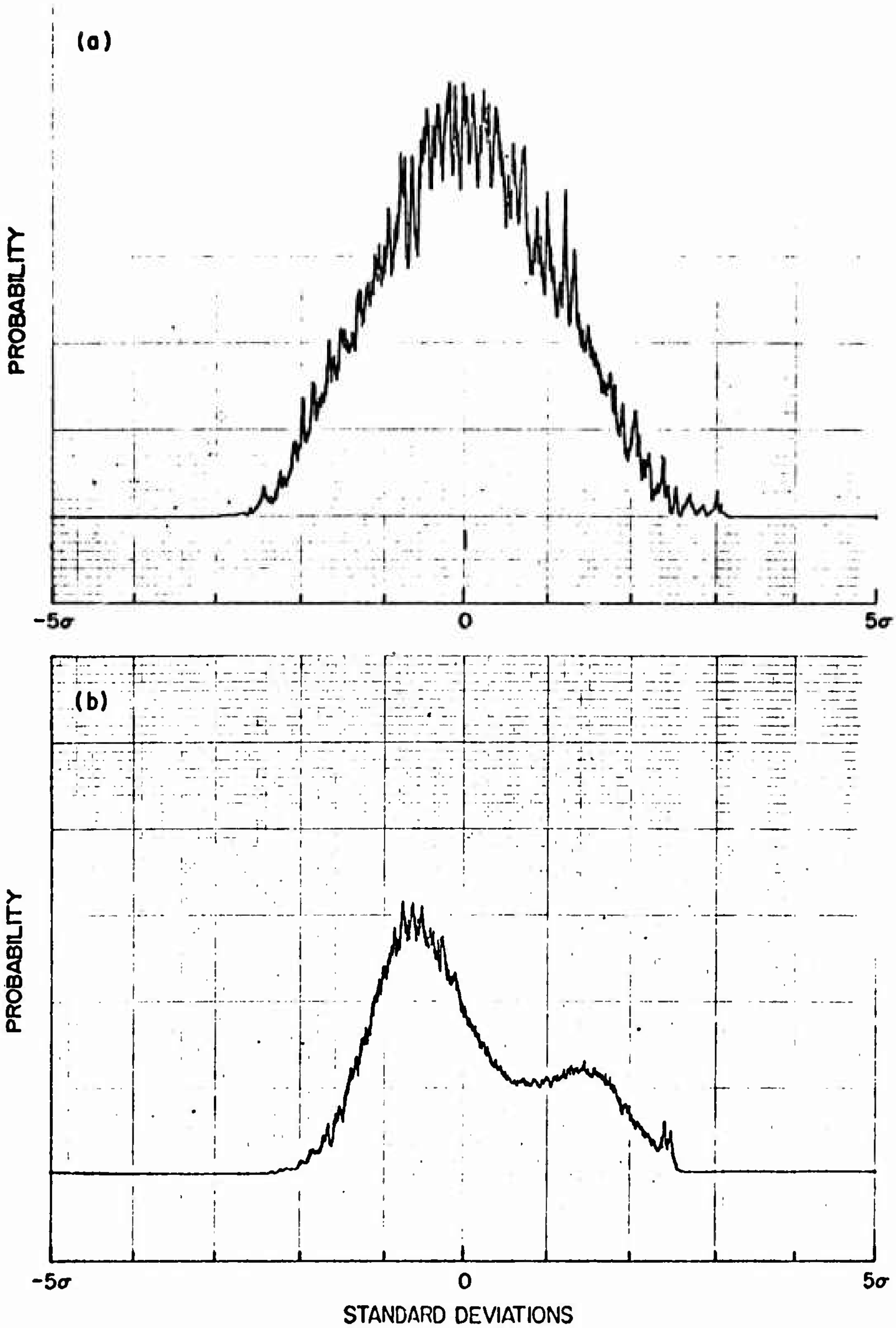


Figure 45. Probability Density Plots for Parameter 61.

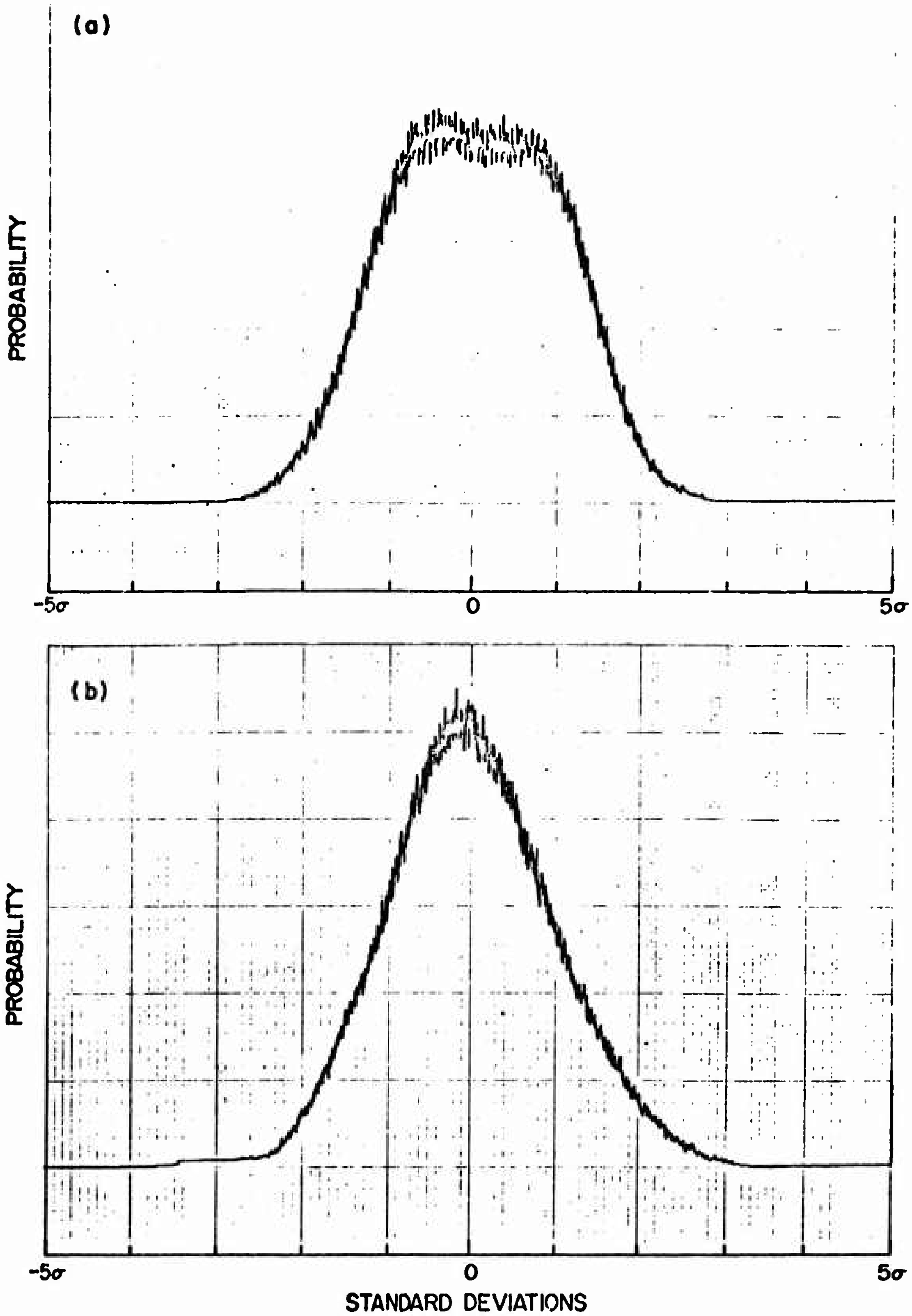


Figure 46. Probability Density Plots for Parameter 126.

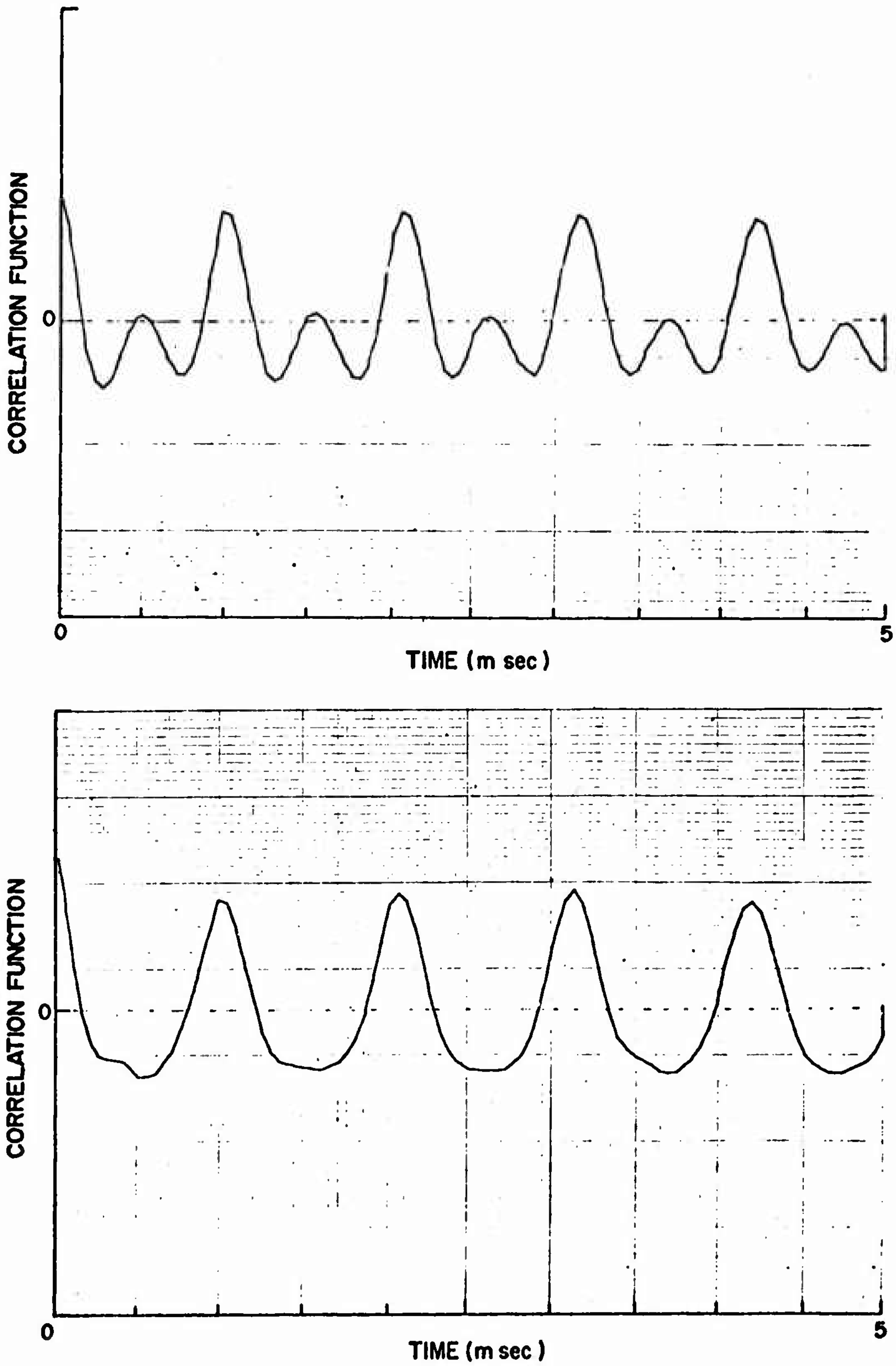


Figure 47. Autocorrelation Plots for Parameter 161.

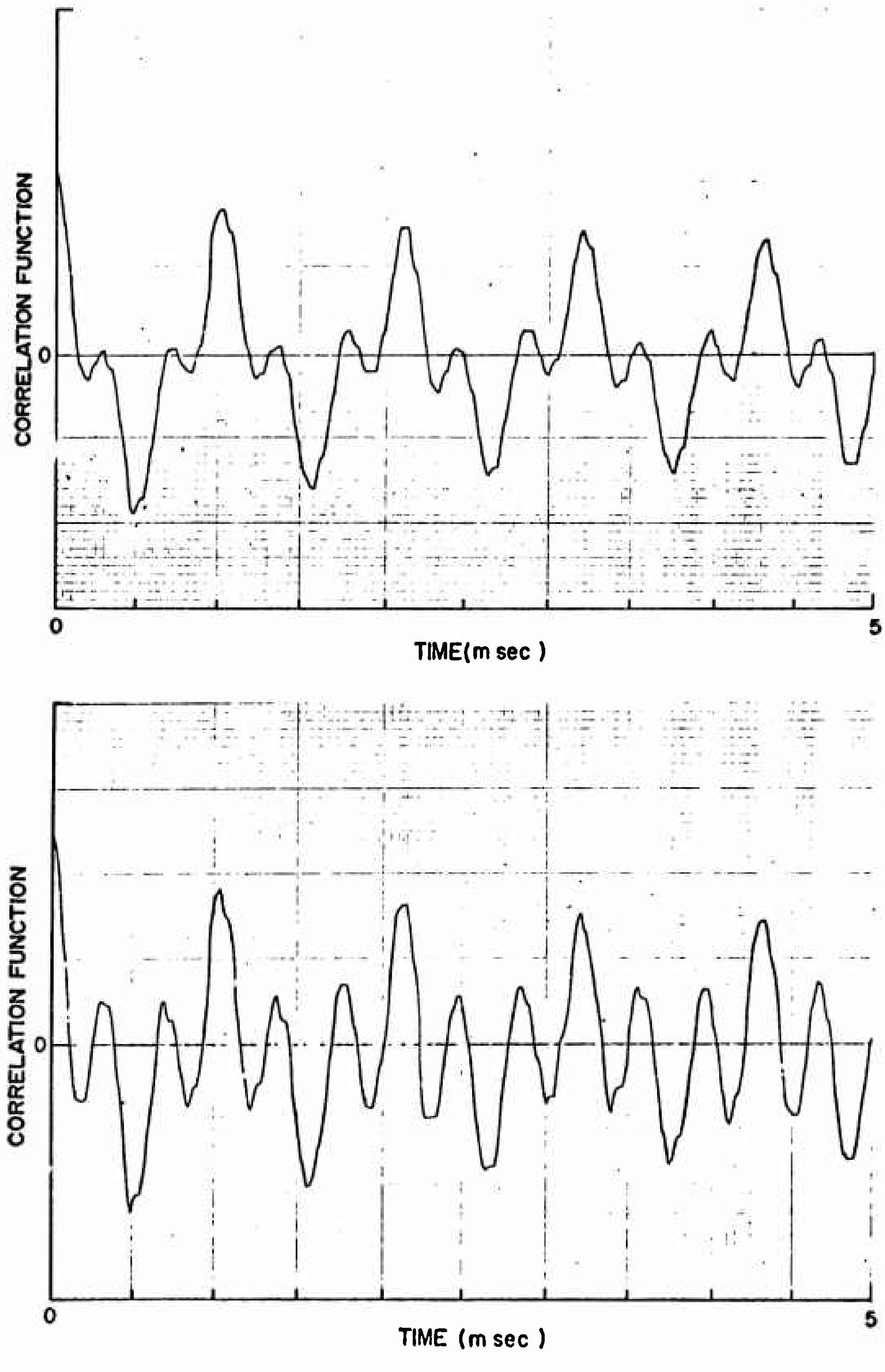


Figure 48. Autocorrelation Plots for Parameter 125.

gearboxes appear to be adequately monitored with a single transducer for each.

AIDAPS Test Bed data was taken from test stand and from actual helicopters in light-on-skids, hover, steady climb, and high-speed level-flight conditions. Spectra for several of the runs were compared in each of these conditions. Spectra for the test stand data differed considerably from the actual helicopter data. Therefore, extra care must be taken in extrapolating test stand results to actual flight conditions. The spectra for the four helicopter operational modes did not differ considerably in overall shape, but amplitudes of individual spectral peaks varied by as much as 6 dB and the shaft speeds shifted slightly. Hamilton-Standard also experienced amplitude calibration difficulties in attempting to use flight-mode baselines to evaluate hover data.

Each sequence of operational modes was performed twice during each test series; i.e., a morning sequence light-on-skid, hover, climb, and level-flight sequence was run and then repeated in the afternoon. Significant differences between these two sequences could not be detected, as spectral peaks had a maximum variation of 2 dB but, typically, did not change more than 1/2 to 1 dB.

In all of the above tests, 64 averages of the real-time spectra were used. Since the data was very stationary and did not have a high random noise content, averages above this number did not improve the spectra. For a lesser number of averages, some variations were observed from one set of averages to the next. These were generally as small as 0-2 dB but were sometimes as high as 5-6 dB for certain spectral frequencies.

In some of the AIDAPS data, baseline runs on the same helicopter, or at least a helicopter having the same engine and transmissions, were performed at two different times separated by several weeks. It was noticed that the spectra differed much more than would be expected in these runs. Peaks which were low in the first run were higher in the second and vice versa. Variations of at least 6 dB were often observed. These variations were of the same level as were typically observed from one good helicopter to another. A study is now in progress in which an attempt will be made to measure the effect of simply removing and installing a gearbox on vibrational spectra. It is being sponsored by USAAVSCOM and is being performed by Parks College of St. Louis University. This study should yield additional information on the effect of gearbox installation on the vibration signatures.

Eleven sets of baseline vibration spectra were analyzed to determine the statistical variations of spectra from one good helicopter to another. Means, Fourier, and PSD amplitudes were computed for each set of spectra. Standard deviation data was also computed. The coefficient of variance, which is the ratio of the standard deviation of each data set to its mean, was computed. The coefficient of variance, $S/\overline{X}$, varies from 0.2 to 3.0 for Fourier amplitudes and from 0.3 to 3.5 for the PSD's. The value of the coefficient of variance is centered in this range in most cases. Typical values for $\overline{X}_u$ and $S/\overline{X}$ for selected peaks of parameter 126, the

accelerometer on the tail rotor quill bearing, are shown in Table IV. The numbering of frequency peaks is shown in the spectrum of Figure 49. It was often noted that each frequency component had one or two values which were extremely high on some baselines. These could be considered either as statistical deviates or the result of parts which were not in as "good" condition as was claimed. An additional computation was made without the deviants and is shown also in Table IV. Typical PSD distributions for frequency numbers 7, 8, 10, and 16 are shown in Figure 50. The deviant effect is clearly shown for frequency bands 7 and 10.

TABLE IV. STATISTICAL VALUES OF SPECTRA FOR PARAMETER 126

	All Ten Values				Excluding High Values			
			PSD				PSD	
Frequency Peak No.	Avg. (g)	$\frac{S}{\bar{X}}$	Avg. (g^2/Hz)	$\frac{S}{\bar{X}}$	Avg. (g)	$\frac{S}{\bar{X}}$	Avg. (g^2/Hz)	$\frac{S}{\bar{X}}$
1	0.24	0.33	0.004	0.66	0.23	0.29	0.004	0.57
2	0.66	0.44	0.03	0.77	0.62	0.44	0.28	0.79
3	0.19	0.58	0.003	1.17	0.17	0.47	0.002	0.89
4	0.79	0.27	0.04	0.53	0.76	0.24	0.038	0.45
5	0.07	0.52	0.0004	1.14	0.065	0.38	0.0004	0.76
6	0.15	0.34	0.002	0.69	0.14	0.33	0.001	0.71
7	0.48	0.42	0.017	1.07	0.42	0.15	0.011	0.29
8	0.47	0.59	0.019	1.08	0.42	0.55	0.014	1.0
9	1.46	0.36	0.165	0.70	1.4	0.37	0.14	0.75
10	1.85	0.57	0.27	1.55	1.5	0.074	0.15	0.15
11	0.77	0.43	0.04	0.87	0.71	0.38	0.035	0.79
12	0.90	0.39	0.06	0.82	0.83	0.32	0.047	0.63
13	0.81	0.66	0.06	1.25	0.72	0.58	0.042	1.2
14	1.36	0.49	0.14	0.94	1.2	0.46	1.2	0.93
15	1.38	0.31	0.13	0.61	1.3	0.28	1.2	0.56
16	9.68	0.27	6.24	0.46	9.3	0.16	6.8	0.34
17	2.45	0.34	0.42	0.63	2.3	0.32	0.37	0.61
18	1.74	0.31	0.21	0.59	1.7	0.29	0.18	0.54
19	0.59	0.41	0.02	0.79	0.55	0.38	0.021	0.76
20	1.75	1.17	0.43	2.18	1.2	0.88	0.16	1.8
21	0.49	0.22	0.02	0.43	0.44	0.19	0.013	0.35
22	1.13	0.89	0.14	1.73	1.1	0.89	0.13	1.8
23	0.50	0.41	0.02	0.75	0.46	0.36	0.015	0.59
24	2.27	0.46	0.38	0.75	2.0	0.47	0.30	0.79
25	0.57	0.33	0.02	0.62	0.53	0.30	0.019	0.56
26	0.64	0.89	0.04	1.45	0.56	0.92	0.034	1.6
27	0.78	0.54	0.05	1.13	0.68	0.41	0.034	0.76
28	0.58	0.68	0.03	1.28	0.53	0.71	0.025	1.5

Helicopter speed variation, which could cause smearing of spectra, was investigated by observing the transmission tachometer signal with a

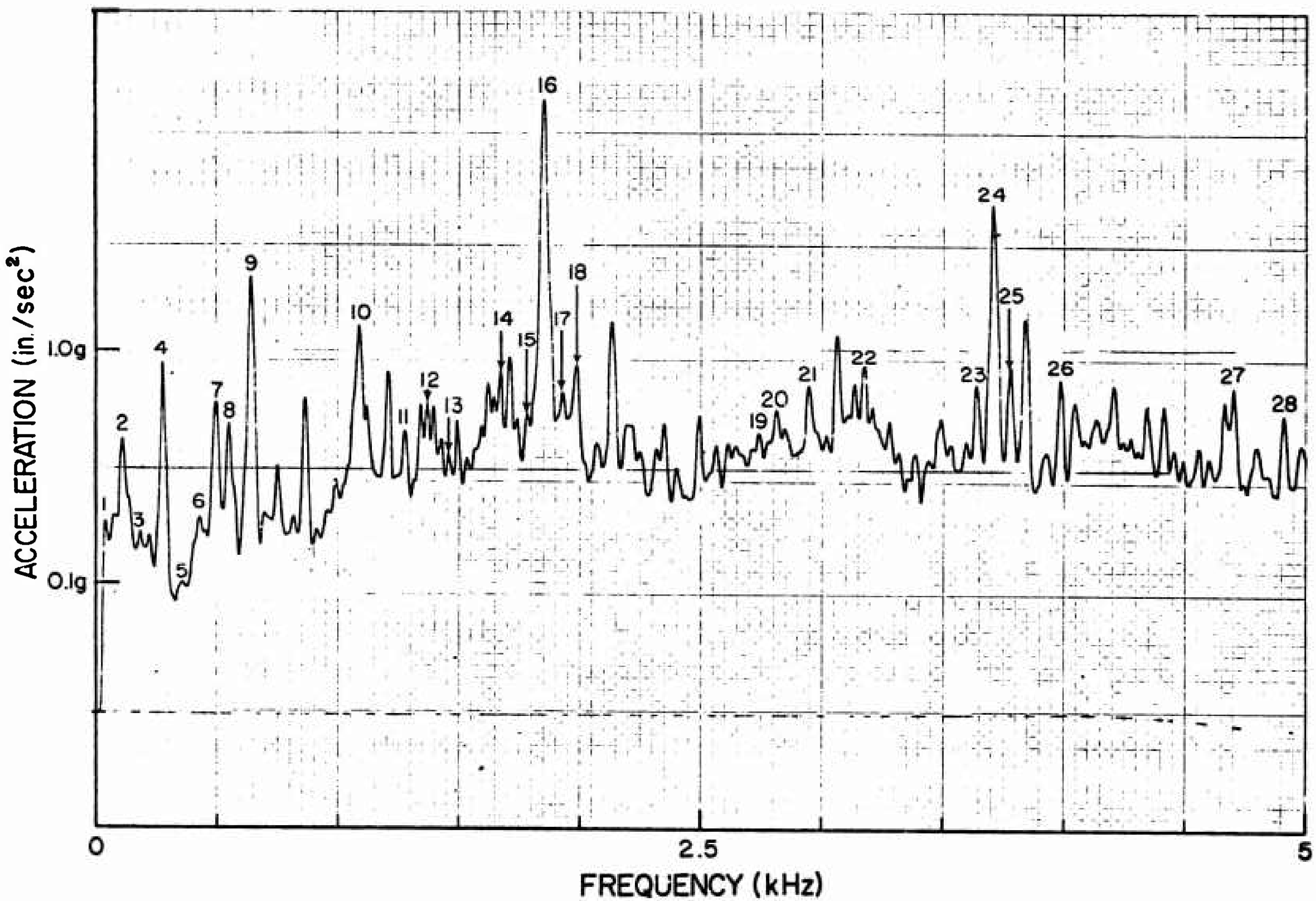


Figure 49. Frequency Peaks Analyzed via Mean and Standard Deviation.

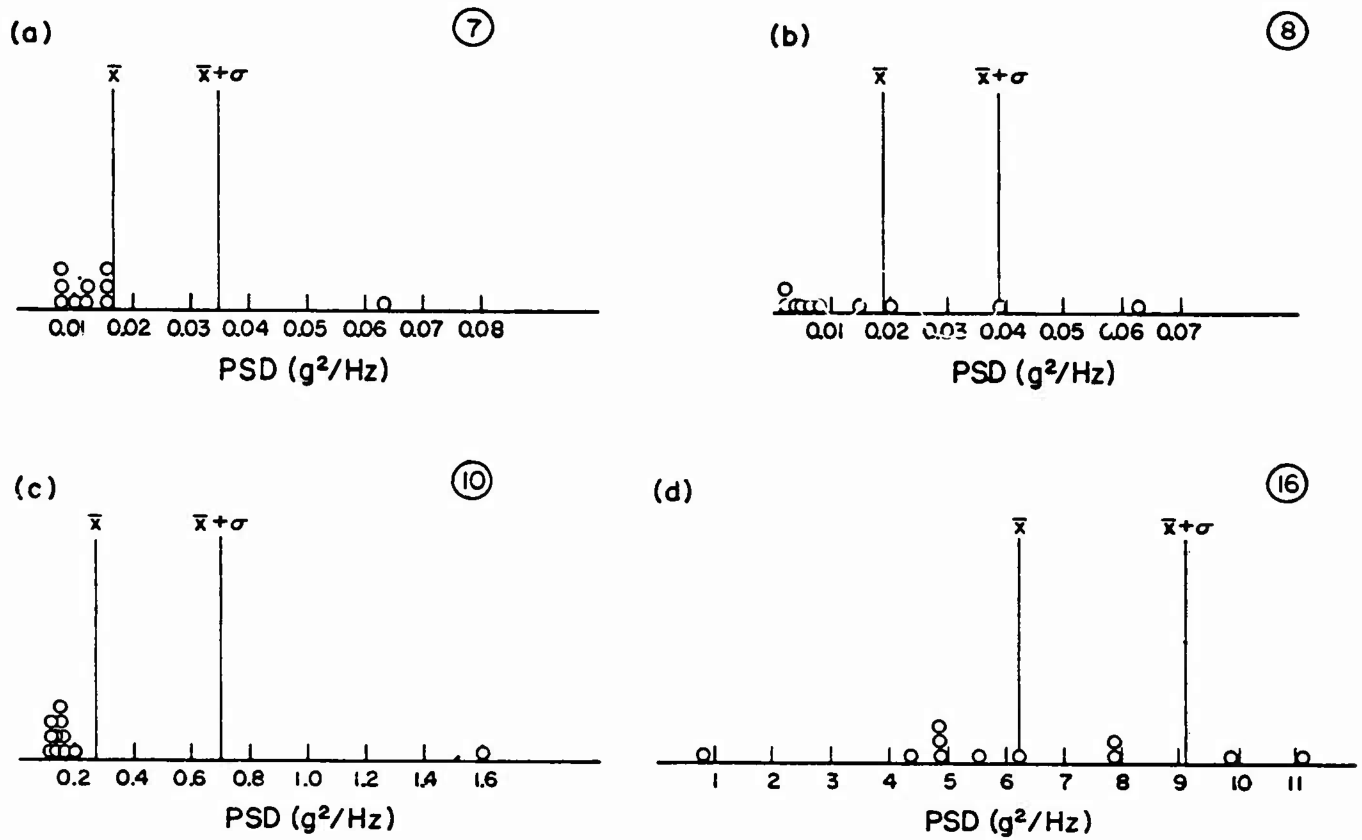


Figure 50. Distribution of PSD Amplitudes for Several Frequencies.

frequency counter. The counter indicated speed variations of an order of magnitude of 1/2 to 1%. This could have the effect of broadening spectral peaks when spectrum averaging is performed. In particular, a 1% speed variation at the higher frequency bands of a 500-point spectrum would cause smearing of a discrete frequency across 4 or 5 frequency bands. This smearing could result in a substantial reduction from actual values in the peak amplitude. However, in comparing single and multiple averaged spectra, the width of frequency peaks tended to remain approximately the same, thus indicating that the speed variations were not as severe as initially thought. A tracking ratio adapter, which compensates for speed fluctuations and normalizes frequency spectra, was attached to the analyzer, but there was virtually no difference in the resulting spectra. In fact, close observation indicated that the spectra were slightly sharper without the adapter. Therefore, it would seem that speed in hover is quite steady during an individual test, but care must be taken to be sure this is the case. Also, speed variations from test to test are likely to occur and should be compensated for.

DIAGNOSTIC TECHNIQUE ANALYSIS FROM AIDAPS DATA

Several of the diagnostic techniques discussed earlier as well as analysis discriminants shown in Figure 26 were investigated with the AIDAPS data. All potential techniques were not tested with this data because its bandwidth limitations were restrictive for some of the techniques. Also, some techniques require special-purpose instrumentation and computational facilities which were not available at OSU.

Narrow-Band Analysis

Narrow-band analysis has been used extensively as a "first attempt" in developing techniques. To investigate this general technique, narrow-band spectra such as those shown in Figures 41 through 44 were plotted for all baseline hover data and the final phase implantations in the test bed program. Plots were always of 500-line spectral resolution in the 0-5 kHz frequency range except for Figure 41a, which is in the 0-500 Hz frequency range.

Attempts were made to identify bearing frequencies associated with specific bearing faults. The frequency resolution of the 5 kHz data is not accurate enough to distinguish between bearing frequencies and other frequencies such as shaft harmonics. Even for narrow bandwidth plots, such as shown in Figure 41a, the bearing frequency is often combined with other frequencies. In general, peaks at bearing frequencies could seldom be located and were generally much smaller in amplitude than other vibration frequencies.

Since no faulty gear implantations were made in the test-bed hover tests, it was not possible to investigate the use of mesh frequencies and their harmonics and sidebands as gearing discriminants. However, the appearance

of these frequency components is certainly apparent and may be of significant value in gearing diagnostics.

Hamilton Standard AIDAPS "4σ" Technique

Attempts made to verify the AIDAPS analysis technique performed by Hamilton-Standard achieved only marginal success. Standard deviations of the power spectral densities of the significant peaks which corresponded to multiples of shaft frequencies were computed; the result of these computations for baseline data was discussed earlier. The value of the mean value plus four standard deviations ($\bar{X} + 4\sigma$) was computed, and all data from faulty part test runs were checked against this value for exceedances. Very few exceedances were noted, and they did not always match those found by Hamilton-Standard. However, when this general technique of counting total exceedances was applied to the data, the result obtained at OSU as to prediction capability was comparable with those of Hamilton-Standard.

However, these differences may have been created by the method of data analysis. Hamilton-Standard used a digital procedure in which 0-5 kHz data was placed in 341 frequency bins. Many of these bins contained data from areas of little or no interest, i.e., valleys between peaks. Also, Hamilton-Standard did not compensate for speed variations from test to test, which could have given some changes in the data. The OSU method was performed from plots made with a real-time analyzer. Only major frequency peaks were included with the OSU analysis. Frequencies were normalized to gear mesh frequencies. This procedure could have changed the data slightly. Finally, errors in calibration could have been made in either analysis procedure.

An interesting comment on the $\bar{X} + 4\sigma$ method is that none of Hamilton-Standard's baselines were flagged as being bad, not even the supposedly statistical deviants. This is a result of the small sample size (10) and the large four-standard-deviation range which was used. In a sample size of 10, the extreme deviant essentially controls the standard deviation value and will always fall within four standard deviations. If two or three standard deviations had been used, there could have been baselines which had frequencies which exceeded these values. In cases where the coefficient of variance is greater than 10, the signal amplitude had to change by about one order of magnitude in order to exceed the $\bar{X} + 4\sigma$ value.

In all instances, the faulty component data looked very similar in form to the baseline data. No new frequency peaks dramatically sprang up from faulty parts. It should also be pointed out that the bad part implants used in this study did not contain gross failures, but typically had one or two small pits on bearing races.

Scope Electronics Optimum Seeking Classifier

In evaluating pattern recognition schemes which were readily available for use in data analysis, the Op-Seeker technique of Scope Electronics seemed

to be a very powerful tool to statistically identify differences in data from two different classes, in this case LRU's containing good and bad parts. Because of the availability of this analysis technique, tapes of data from the AIDAPS program were made, as described in Appendix III, and sent to Scope for evaluation. Appendix V contains a report submitted by Scope on the analysis of the 42° gearbox using this data. Because of a tape speed change in the duplication of data, all frequencies in the Appendix are one-half the actual frequency values.

This data analysis, which was not very extensive, achieved a similar prediction capability to Hamilton-Standard and Northrop and ranked the features of prime importance in the classification.

The "Op-Seeker" program is designed to order 20 features which the operator may choose. In the first set, the features chosen were all discrete frequencies related to gears and bearings in the 42° gearbox. In this analysis, two of the most significant features were found to be ball-pass frequencies of two bearings in the 42° gearbox. This point proved to be very interesting, since ball-pass frequencies were hardly discernible on typical spectra observed by OSU. Apparently the changes at these frequencies are adequate to be distinguished by the pattern recognition technique.

In the second set of features used, ranges of frequencies identified by Northrop were included as features to be ranked. Here, four of the first five ranked features were sidebands of the 42° gearbox mesh frequency and its first harmonic. A similar observation regarding the effects of bearing faults on gear mesh frequencies and sidebands was made by Hamilton-Standard. The feature ranking second corresponded with one of Northrop's chosen ranges. It should be pointed out that the features used are not optimum, but only first trials which could be improved by more judicious feature selection.

The fact that the same data was used in the training set as was used to test the classifier also tempers these results. In order to obtain a truly unbiased analysis, unknown data would have to be supplied to the classifier. However, a large enough volume of data was not available to do this.

Probability Density Analysis

Probability density functions were plotted for a small sample of the good and bad parts. As pointed out earlier, these plots often appeared Gaussian. At other times these plots were non-Gaussian, tending to flatten out or to display double peaks. The occurrence of a double peak did not correlate either positively or negatively with the presence of bad parts nor was it consistent with the transducer location being used.

Perhaps pre-whitening of the data by band-pass or notch filtering would condition the data so that valid discriminants could be obtained by this analysis technique.

Impact Index

Impact indexes were computed from the raw data simply by reading the peak values from an oscilloscope trace and reading rms values from a meter. The impact indexes were then calculated by taking the ratio of peak/(2•rms value). For all of the data, whether with good parts or bad parts, the impact indexes ranged in value from 1.0 to 3.5 with most of the values falling below 2.0. None of these values approached the "bad bearing" limit of 5.0 set by G.E.

The primary reason for this discrepancy is that the vibration signals were so dominated by the gear mesh frequencies that they were essentially sinusoidal in nature. Any transients created by bearing impacts are so small that they did not affect the vibration signal.

Two types of modification might condition the data for impact index analysis. The first would be to filter out the gear mesh frequencies and their harmonics from the data. The second technique would require time averaging the data at a rate commensurate with the bearing pass frequencies.

Correlation

Again, due to the predominance of gear mesh frequencies, the correlation analysis did not show significant differences between good and bad parts.

Cross-correlation of good and bad part signals was performed by recording good and bad data on parallel channels of analog tape. The cross-correlation functions were not always stable, possibly because the helicopters were operating at slightly different speeds. In general, the cross-correlation function plots were similar to the autocorrelation function plots.

Other Techniques

Two other functions were computed for the parallel recorded data. The first was a cross power spectral density function between two sets of good runs and between a set of good and a set of bad runs. Figure 51 shows a cross power spectral density function between two good runs, and Figure 52 shows a cross power spectral density function between one of the good runs and a bad part run. The data is for a transducer located on the tail rotor output of the main transmission. Peaks are rather sporadic but typically occur at the frequencies at which amplitudes are greatest in the frequency spectra of individual runs. Differences can be observed in the plots. A coherence function was also computed for the same data, but it did not indicate coherence at very many frequencies and, in general, was very noisy and difficult to interpret.

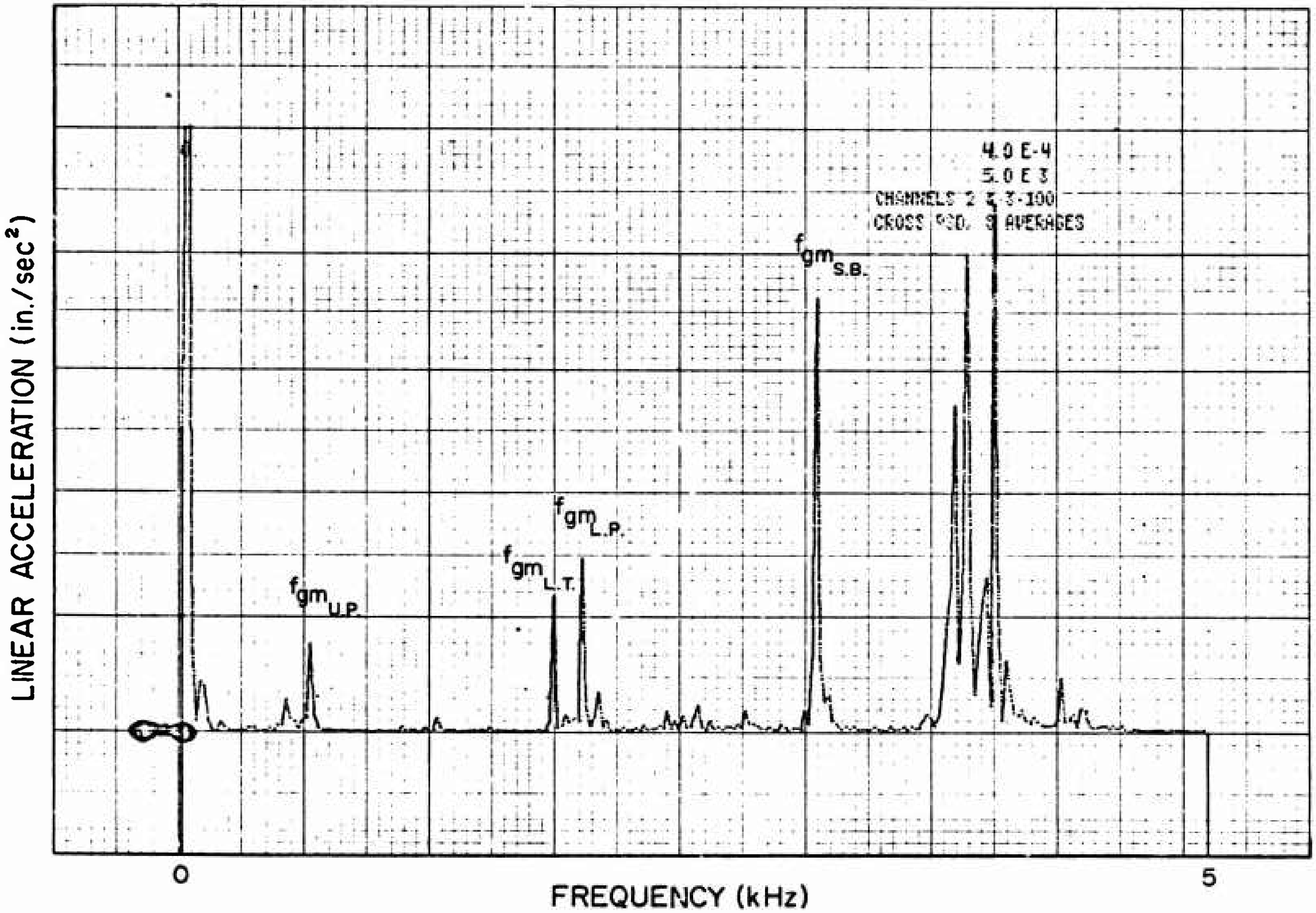


Figure 51. Cross Power Spectral Density Plot Between Two Good Runs (Upper Mast Vibration).

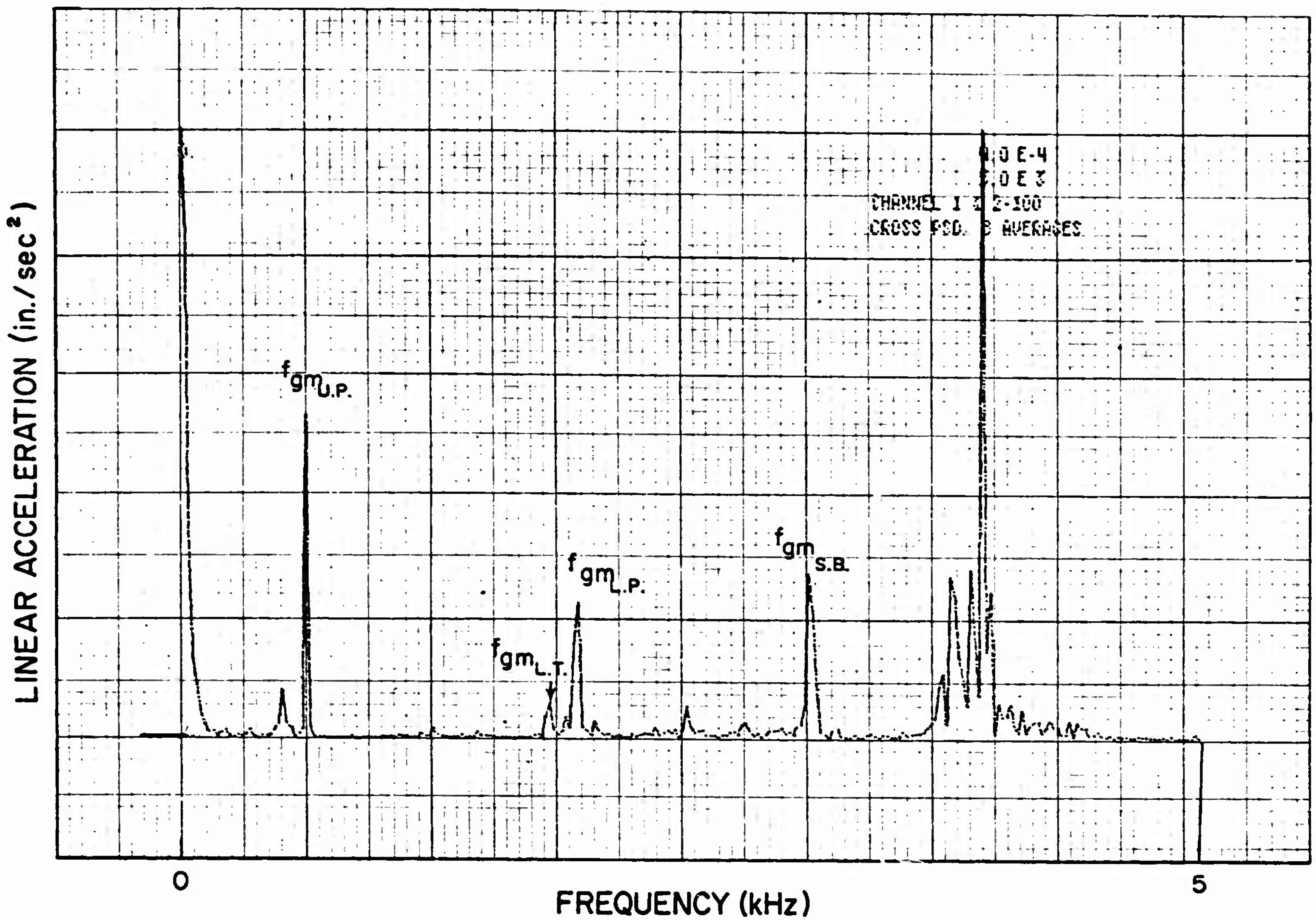


Figure 52. Cross Power Spectral Density Plot Between a Good Run and a Bad Run. (Upper Mast Vibration)

BEARING TEST RIG

The vibration data from helicopter power trains (as available from the AIDAPS Test Bed Program) was bandwidth-limited to 5 kHz. A number of the diagnostic techniques use, as a physical basis, phenomena which occur above the 5 kHz limit (MTI bearing ringing, SKF shock pulse, to some extent G.E.'s impact index, and others). Bearing vibration data was generated at frequencies up to 50 kHz to properly evaluate the capabilities of these techniques and to further analyze other techniques.

The test stand, as shown in Figure 53, was used to generate the bearing vibration data. The system is driven by a 1750-rpm, 1/3-hp electric motor. Bearings are mounted in four pedestals supporting the two shafts. The bearing used in most of the tests was a Norma-Hoffman L-25 angular contact ball bearing. The two shafts are connected by a gear pair with available ratios of 1:2, 1:1, and 2:1. If desired, the gears may be disconnected completely. Load is applied to the system via a hydraulic pump. This nine-cylinder pump is connected to the rest of the system with a timing belt. The amount of load applied by the pump can be controlled by a throttle valve with a pressure gauge monitoring the load level. Accelerometer stud mounts are placed at various positions on the rig.

Narrow-Band Analysis

A narrow-band analysis was performed as an initial step in the evaluation with the test rig. Table V gives the frequencies which may be associated with given system components. Figures 54 through 60 show spectra of the vibration signal generated under various conditions of bearing health. All of the spectra presented in these figures were run with the gearing disconnected and, thus, no loading via the pump.

Figures 54 and 55 show the spectra of a "good" bearing, with Figure 54 covering the range from 0-1 kHz and Figure 55 the range from 0-5 kHz. A "good" bearing is described as one which, when visually inspected, exhibits no faults. The only easily discernible spectral components that appear in Figure 54 are the shaft frequency and its harmonics. In Figure 55, two additional strong peaks of interest appear: at 8800 Hz, a peak which was determined to correspond to a resonance in the test rig structure appears; and at 22 kHz, a peak which might correspond to a higher order "ring" resonance of the bearing occurs. The exact origin of this frequency component has not been determined, but it corresponds to the computed value for the fourth resonance of the bearing outer race.

Figures 56 through 60 show spectra for bearings exhibiting faults. These faults were of the following form:

1. Inner Race Fault: a line was scribed across the inner race.

2. Outer Race Fault: a line was scribed across the outer race.

3. Ball Fault: A facet was filed onto one of the balls.

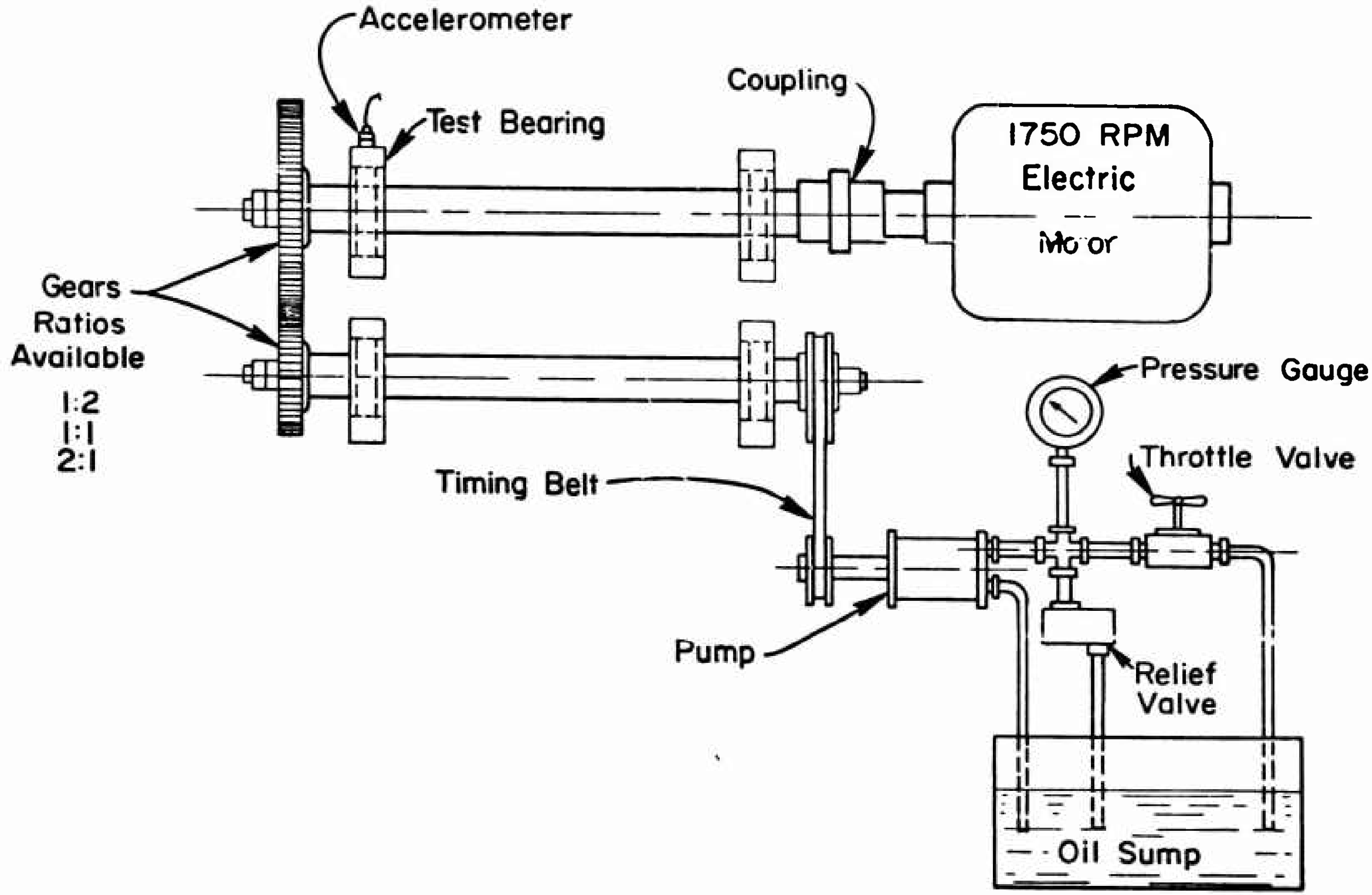


Figure 53. Bearing Test Rig.

TABLE V. CALCULATED CHARACTERISTIC FREQUENCIES FOR THE TEST RIG

Bearings

$$f_{or} = \frac{n}{2}\frac{N}{60}\left(1 - \frac{2r}{D}\cos\beta\right) = 140.7 \text{ Hz}$$

$$f_{ir} = \frac{n}{2}\frac{N}{60}\left(1 + \frac{2r}{D}\cos\beta\right) = 209.3 \text{ Hz}$$

$$f_b = \frac{D}{2r}\cdot\frac{N}{60}\left(1 - \left(\frac{2r}{D}\right)^2\cos^2\beta\right) = 138.2 \text{ Hz}$$

$$f_{cage} = \frac{N}{120}\left(1 - \frac{r}{D}\cos\beta\right) = 11.7 \text{ Hz}$$

$$f_{ball\ res.} = \frac{0.848}{2r}\sqrt{\frac{E}{2\rho}} = 387{,}459 \text{ Hz}$$

$$f_{race\ res.} = \frac{k(k^2 - 1)}{2\pi\sqrt{k^2 + 1}}\frac{1}{a^2}\sqrt{\frac{EI}{m}}$$

a) outer race:

k = 2: 3,938 Hz
k = 3: 11,137
k = 4: 21,355
k = 5: 34,536
k = 6: 50,663

b) inner race:

k = 2: 9,742 Hz
k = 3: 27,555
k = 4: 52,834

Gears

$$f_{gm} = \frac{N}{60} \times \text{no. teeth} = 2{,}33 \text{ Hz}$$

Belt

$$f_{belt} = \frac{N}{60} \times \text{ratio of teeth} \times \text{no. sprockets} = 975 \text{ Hz}$$

TABLE V - Continued

Pump

$$f_{pump} = \frac{N}{60} \times \text{ratio of teeth} \times \text{ratio of sprockets} \times \text{no. of cylinders} = 730 \text{ Hz}$$

Shaft

$$f_{sr} = \frac{N}{60} = 29.17 \text{ Hz}$$

$$f = \frac{\lambda^2 \pi^2}{\ell^2} \sqrt{\frac{EI}{A\rho}} \quad \text{where } \ell = \text{c/c bearings, in.}$$

$$= \lambda^2 (3000)$$

$\lambda = 1$: 3000 Hz

$$f_{sb} = f_{gm} \pm f_{sr}$$

$$= 2{,}333 \pm 29.17$$

Nomenclature for Table V

r	= ball radius, 0.15625 in.
D	= bearing pitch diameter, 1.540 in.
β	= contact angle, 15 degrees
n	= number of balls, 12
N	= 1750 rpm
E	= modulus of elasticity = 30,000,000 psi
ρ	= ball density = 0.284 lb per in.^{3}/386 in. per sec^2 = 0.000735 slug/in.^{3}
k	= number of waves around circumference of ring, 1, 2, 3, ...
I	= moment of inertia of cross-sectional area about the neutral axis; outer race = 0.000115 in.^{4}, inner race = 0.0000868 in.^{4}
a	= radius to the neutral axis: outer = 1.853 in., inner = 1.227 in.

TABLE V - Continued

m	= mass of ring per linear inch, 0.00005 slug/in.
f_{or}	= outer race frequency
f_{ir}	= inner race frequency
f_b	= ball-pass frequency
f_{cage}	= cage-pass frequency
$f_{ball\ res}$	= ball resonance frequency
$f_{race\ res}$	= race resonance frequency
f_{gm}	= gear mesh frequency
f_{belt}	= belt frequency
f_{pump}	= pump frequency
f_{sr}	= shaft rotational frequency
f_{sf}	= shaft flexural frequency
$f_{s.b.}$	= sideband frequency

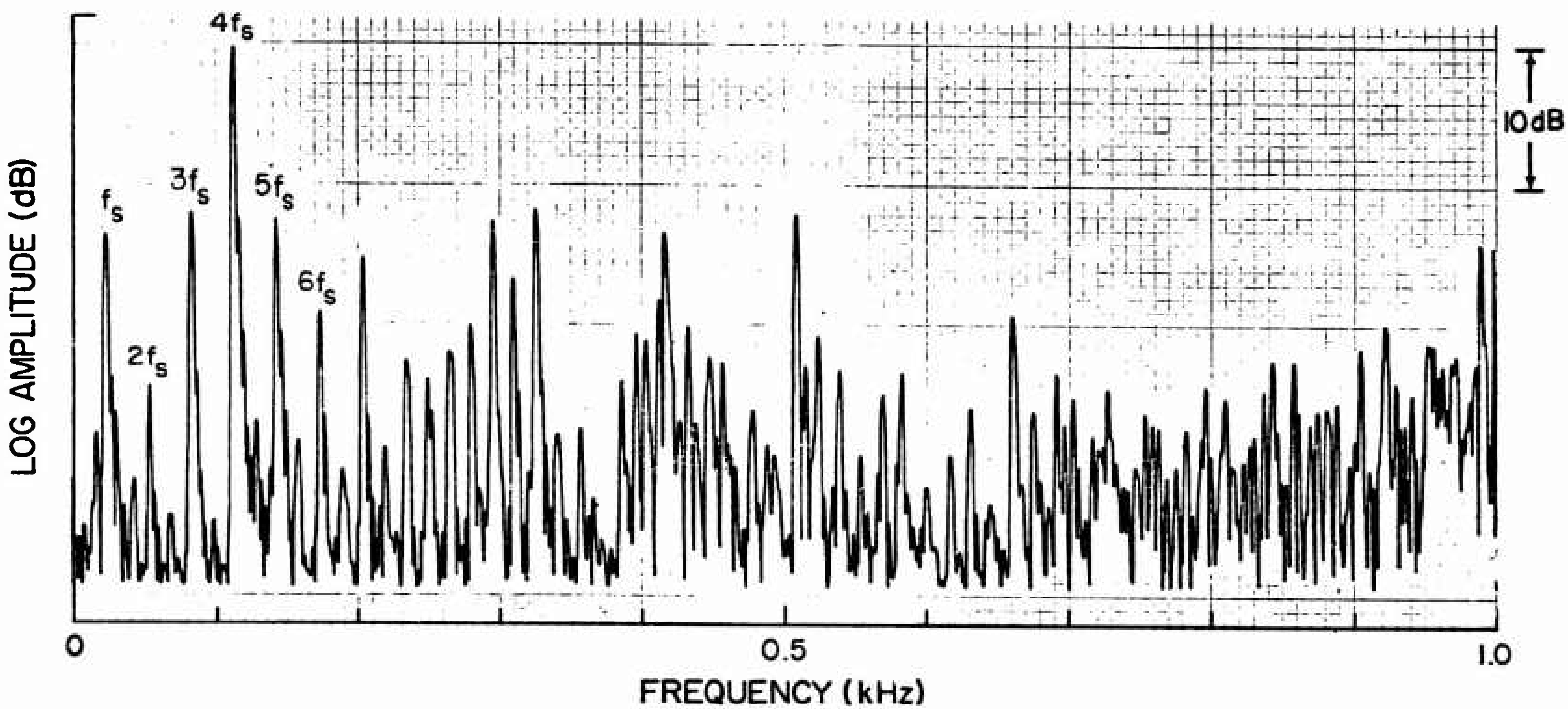


Figure 54. PSD of a Good Bearing (0-1 kHz).

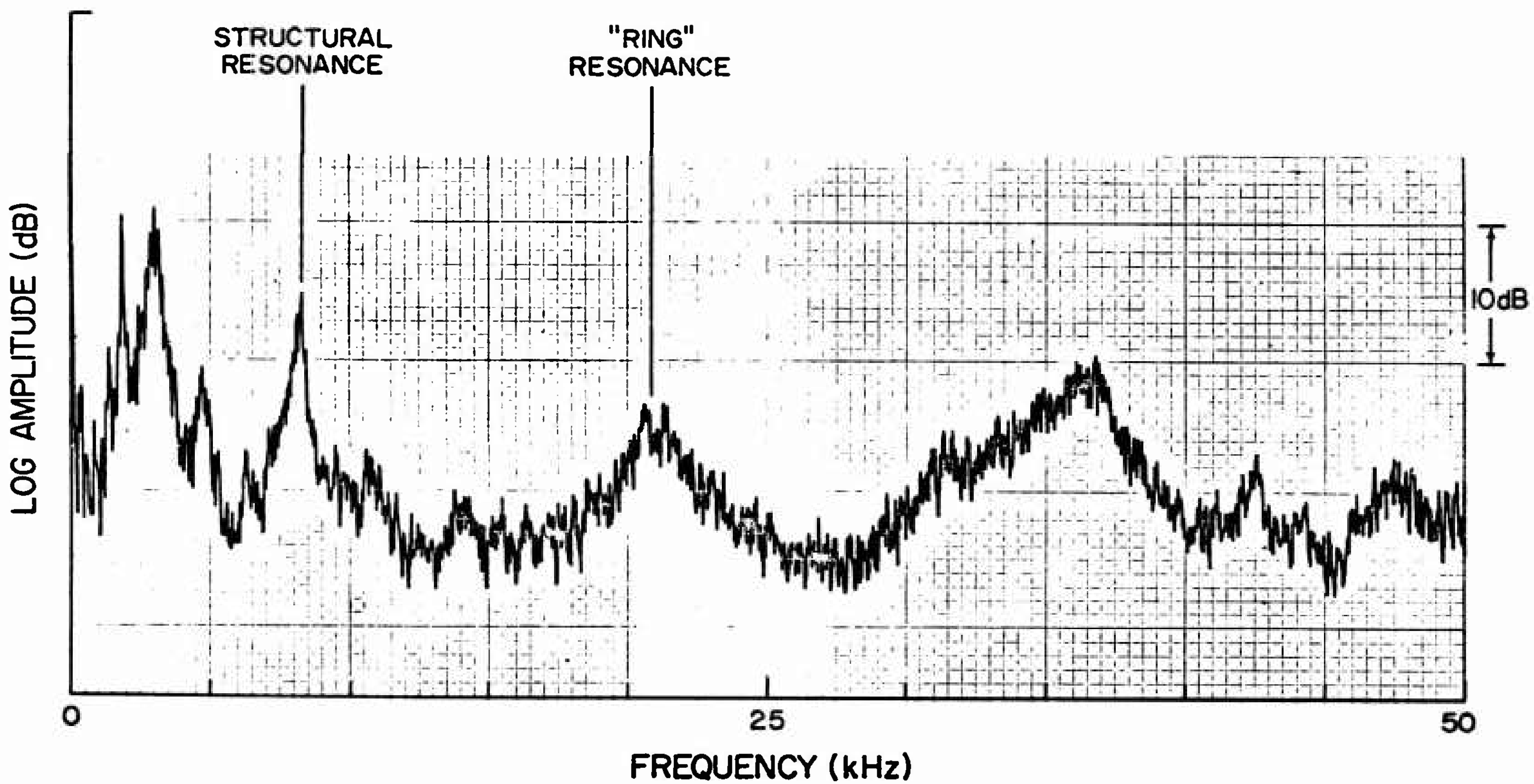


Figure 55. PSD of a Good Be··ing (0-50 kHz).

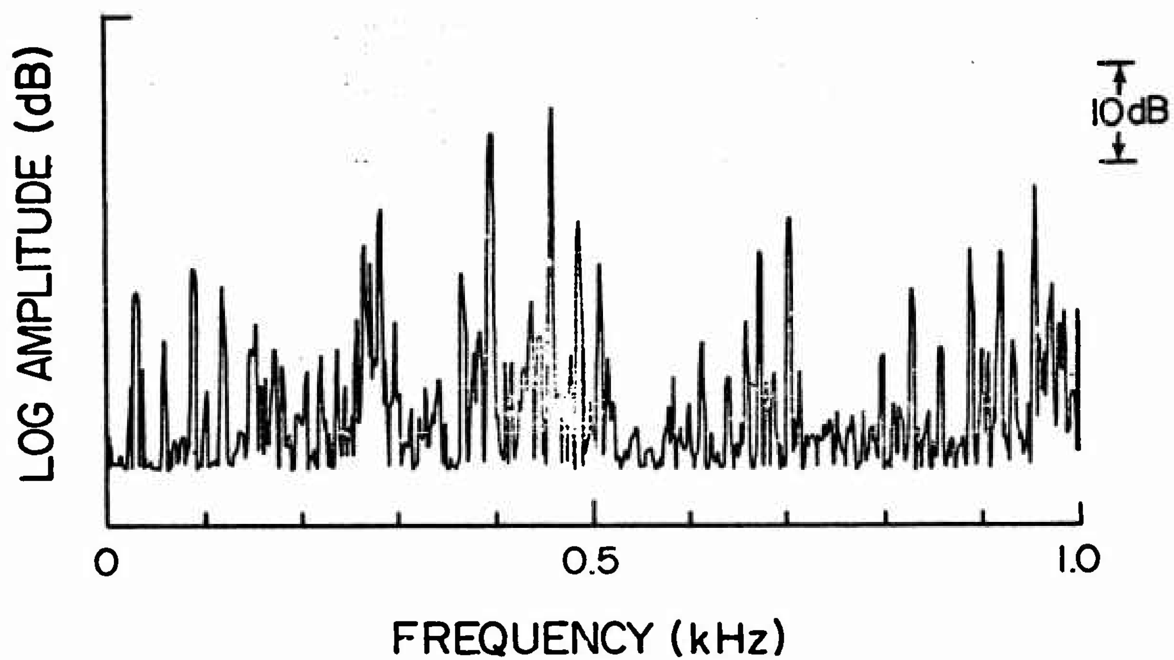


Figure 56. PSD of Bearing with Bad Inner Race (0-1 kHz).

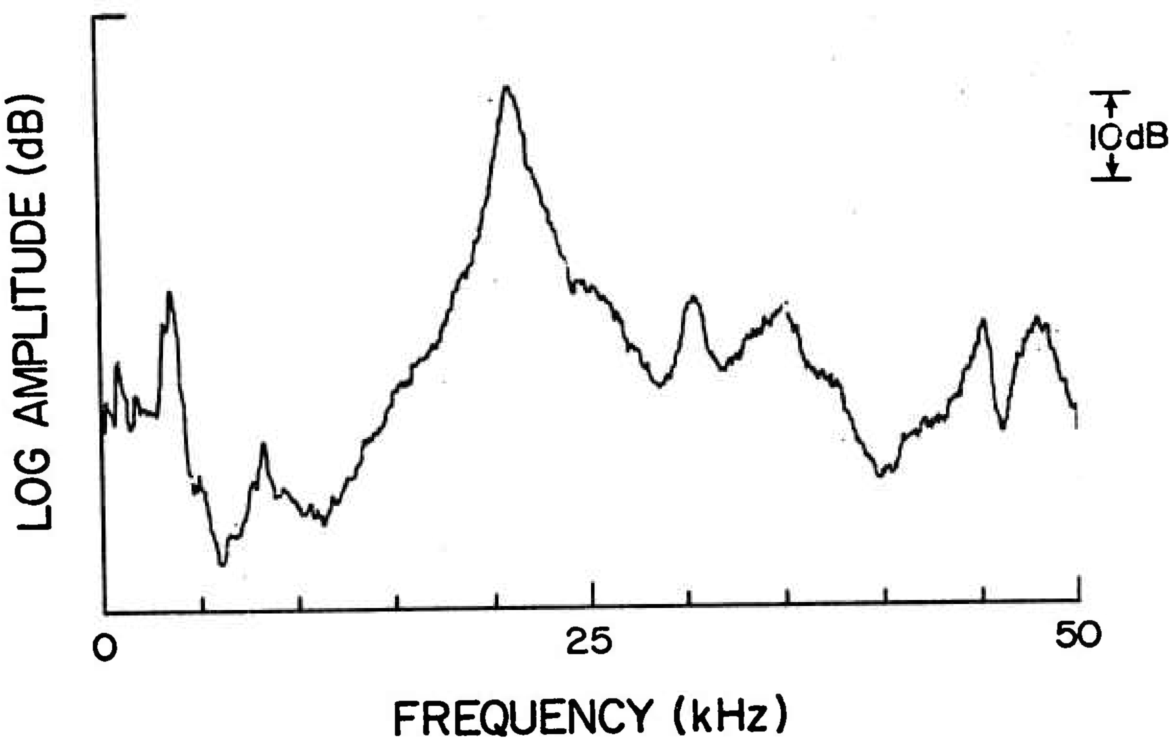


Figure 57. PSD of Bearing with Bad Inner Race (0-50 kHz)

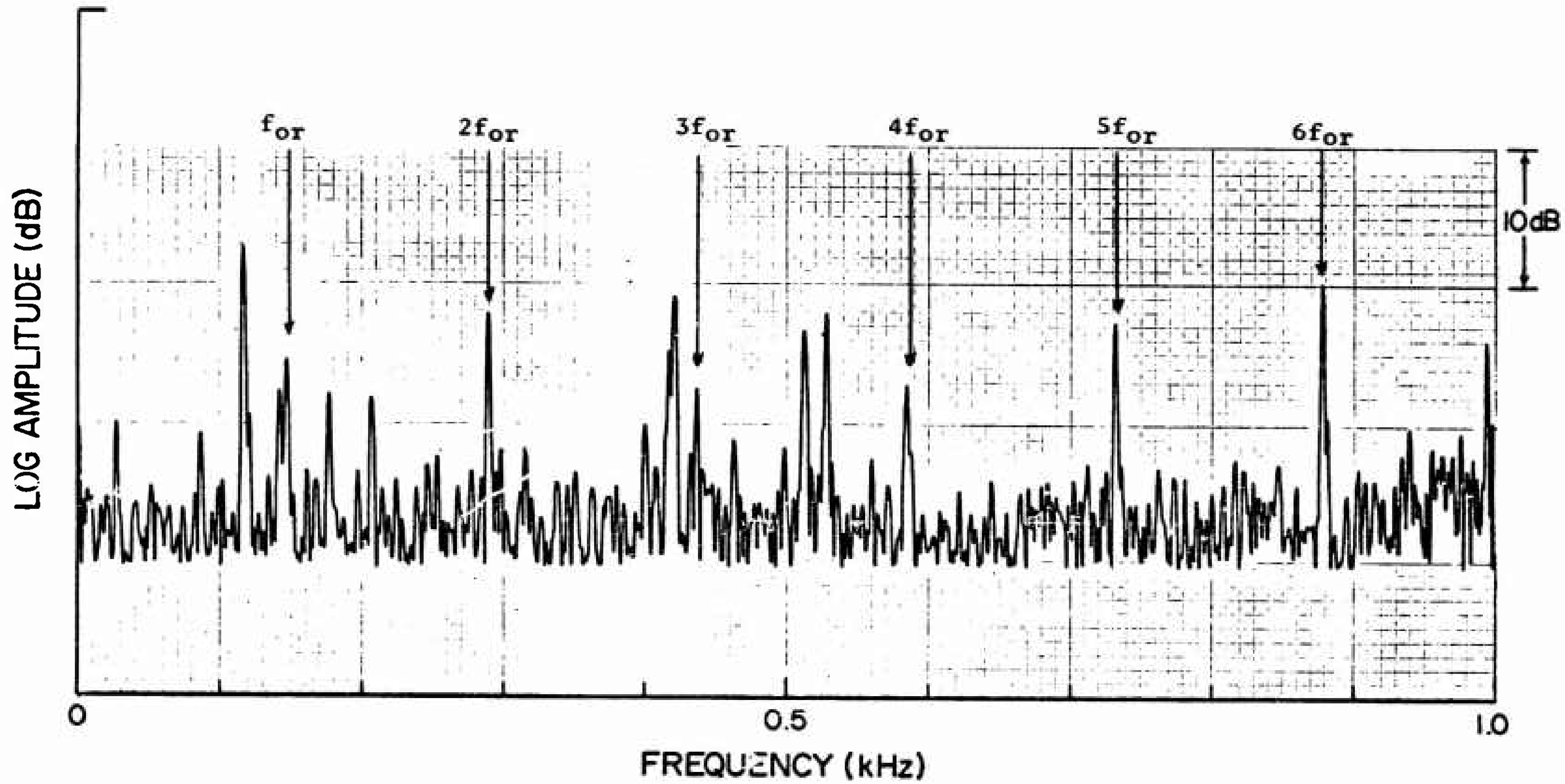


Figure 58. PSD of Bearing with Bad Outer Race (0-1 kHz).

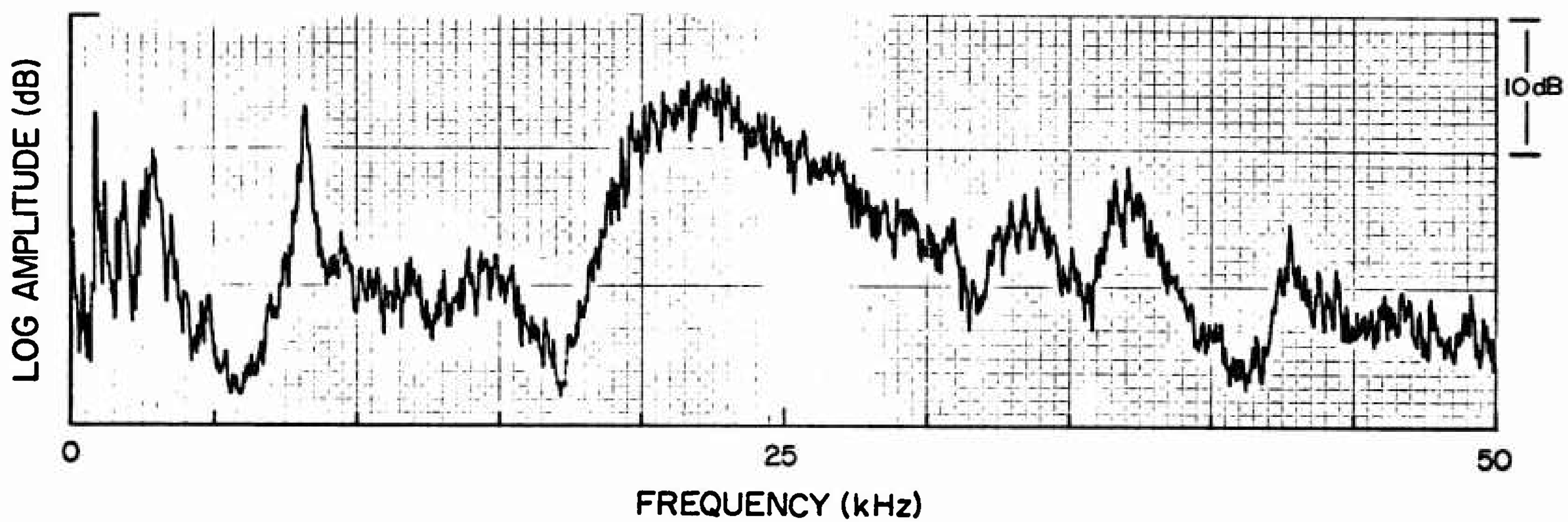


Figure 59. PSD of Bearing with Bad Outer Race (0-50 kHz).

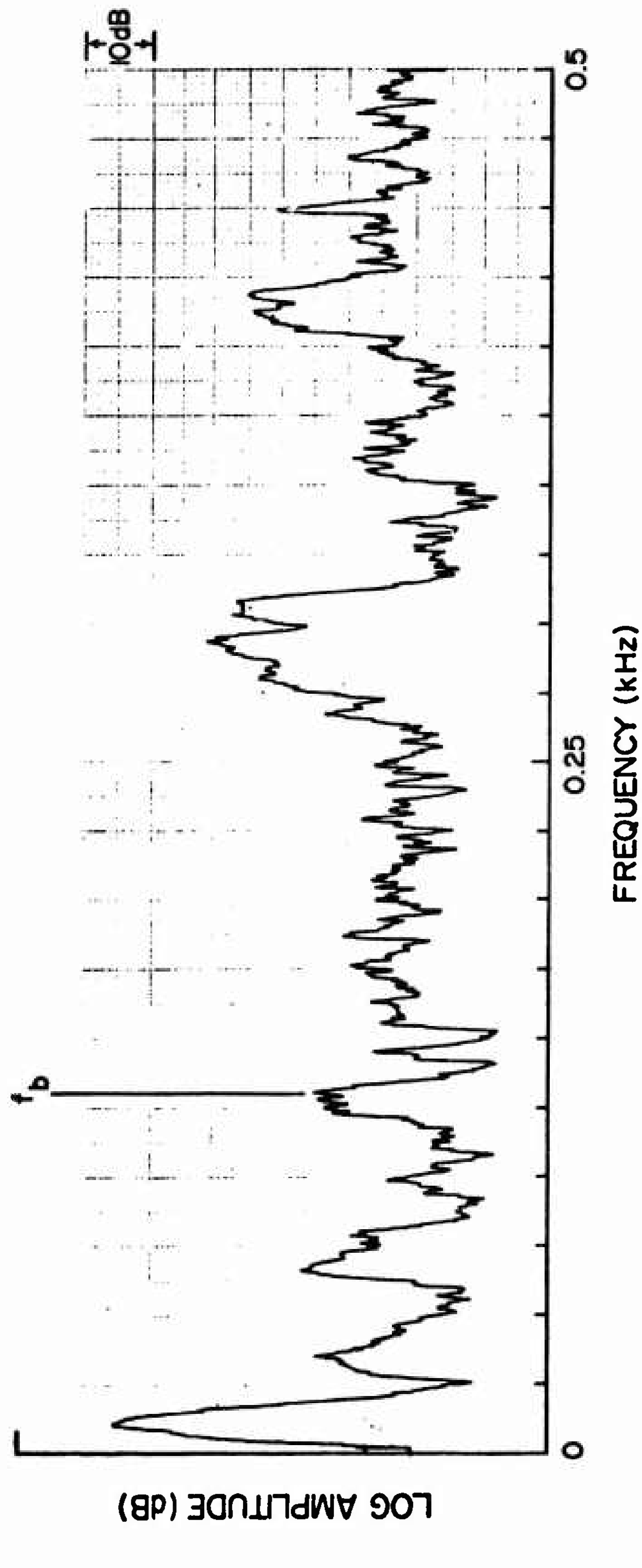


Figure 60. PSD of Bearing with Faulty Ball (0-500 Hz).

In Figure 56 (0-1000 Hz), the inner race frequency peak is not readily evident. However, in Figure 57 (0-50 kHz), the 8-kHz peak appears as does the 22-kHz peak, which typically increased in amplitude by some 20-40 dB over the good bearing.

Figure 58 (0-1000 Hz) shows the spectrum for a bearing having an outer race fault. A peak at 140 Hz which corresponds to the outer race frequency is observed. Harmonics of that frequency are also very evident. In Figure 59 (0-50 kHz), both the 8-kHz and the 22-kHz peaks again appear with increased amplitude. Here, the 22 kHz is slightly broader. Figure 60 (0-500 Hz) shows the spectrum for a bearing exhibiting a ball fault. The ball-pass frequency may be observed at 135 Hz.

Bearing "Ringing"

One of the purposes of the test rig work was to examine high-frequency bearing vibration phenomena, particularly the "ringing" mentioned by MTI. Figures 61 and 62 show the "ringing" response as exhibited on the test rig when an inner race fault was implanted. The higher frequency of oscillation corresponds to the 22-kHz peak seen in the frequency spectra. As seen in Figure 61, the repetition rate of impact corresponds to the inner race frequency.

It was found that the "ring" was produced at approximately the same frequency for all the faults in the particular bearing being used. Other bearings produced a "ring" but at different frequencies. The exact frequency of the "ring" cannot be predicted by computation but does, as mentioned earlier, match up well with the computed value for the fourth natural frequency of the outer race as computed from Equation (6). The reason for the first, second, and third natural frequencies' not being present is subject to debate. A cause could be that the bearing housing tends to dampen these lower frequency motions, and only the fourth natural frequency can be excited in its free-free mode. The amplitude of motion is very small at the accelerometer location (0.1 μin.) at 22 kHz and tends to indicate that uncoupled vibration of the race may be possible.

Table VI shows a calculation of the race resonances for a variety of bearings found on the UH-1 helicopter. Again it would be impossible at this time to predict which resonant frequency on any of these bearings might be excited by a fault.

By examining the time traces of Figure 61 or Figure 62, modulations and phase reversals appear; an explanation of these has not been found.

It is seen from Figures 61 and 62 that the transient builds up gradually before decaying. This observation is contrary to the free response of most structures to short-duration pulse forces, since the typical response has its maximum amplitude on the first oscillation after impact. In this instance it might indicate that the bearing force created by the impact is not a single pulse, but several pulses, the first occurring when the ball contacts the leading edge of the fault and the second when the ball impacts

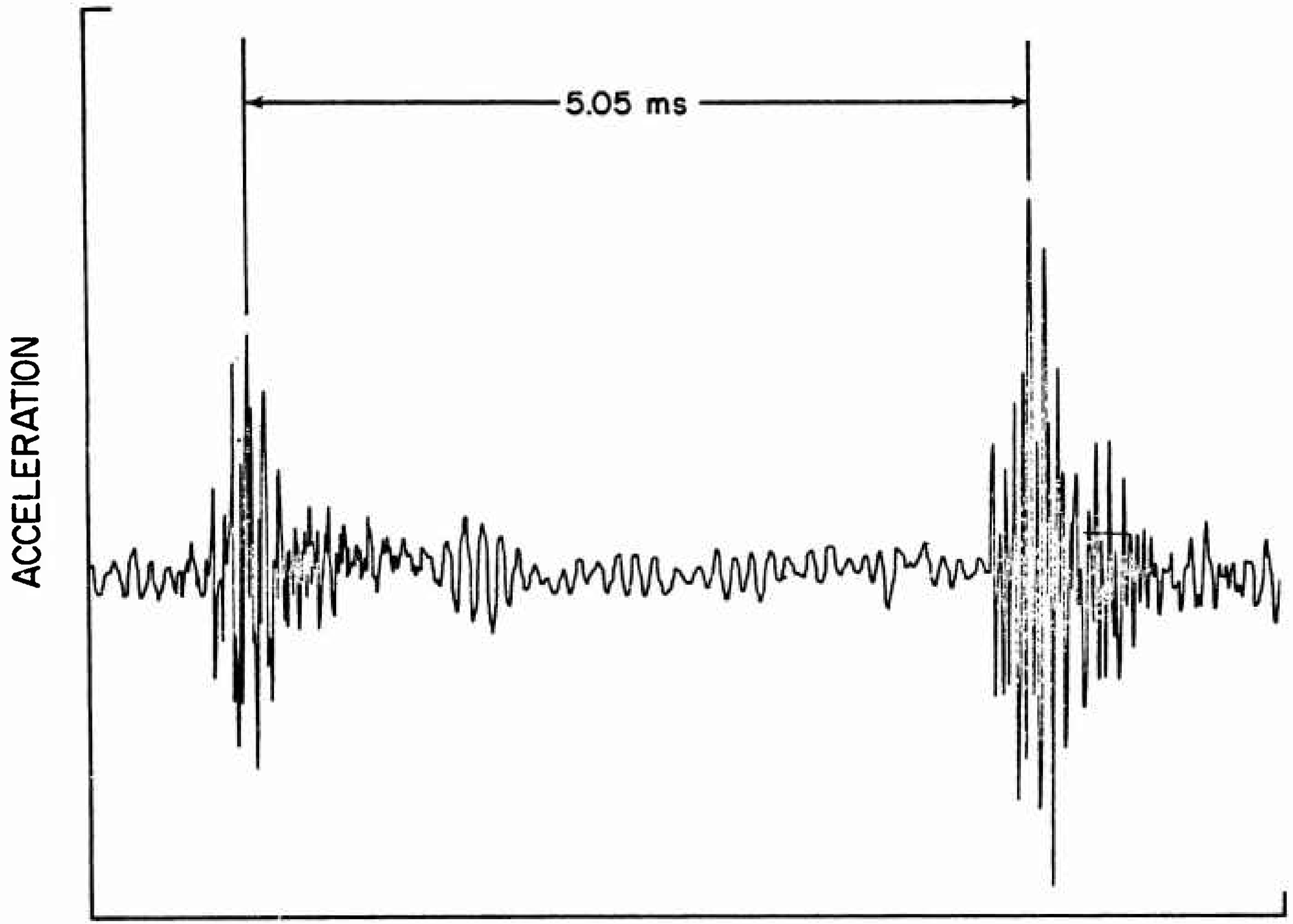


Figure 61. Time Response of Bearing "Ring" for Two Impacts.

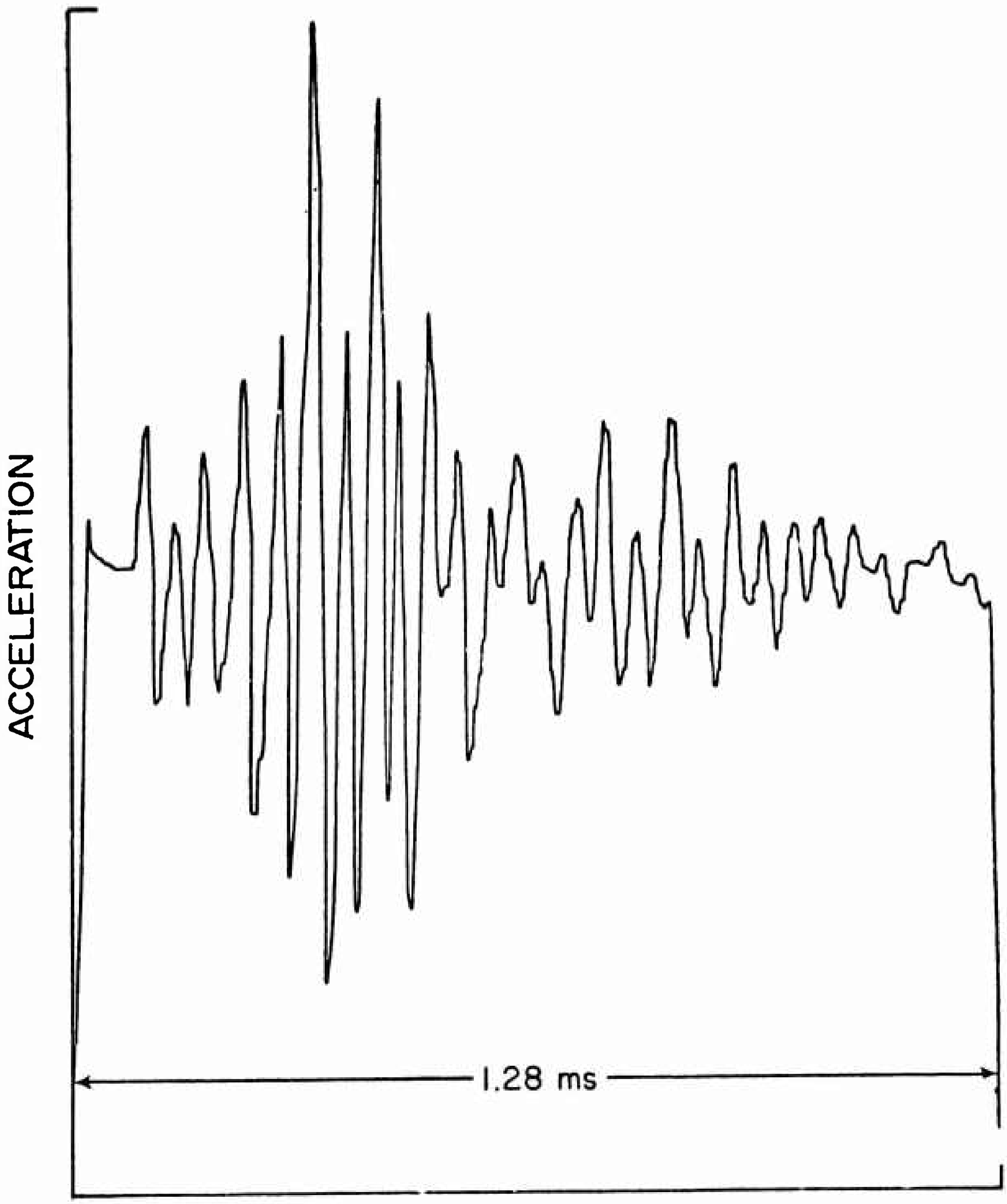


Figure 62. Time Response of Bearing "Ring" for Single Impact.

TABLE VI. RACE RESONANCES AS CALCULATED FOR BEARINGS FOUND ON THE UH-1H HELICOPTER (RESONANCE FREQUENCIES, kHz)

Bearing Data Helicopter Model Drawing No. Bearing Type		1 UH-1 204-040-142-1 Ball		2 UH-1 204-040-346-3 Triplex Ball		3 UH-1 204-040-271 Cylin. Roller		4 UH-1 204-040-135 Ball		5 UH-1 204-040-135 Ball		6 UH-1 204-040-143 Duplex Ball		7 UH-1 204-040-406 Cylin. Roller	
Race: I = Inner O = Outer		I	O	I	O	I	O	I	O	I	O	I	O	I	O
Mode No:	2	3.00	2.65	2.54	1.31	No	0.99	0.95	0.67	1.49	0.80	7.82	3.16	16.89	6.18
	3	8.50	7.51	7.18	3.71	inner	2.80	2.68	1.90	4.21	2.25	22.11	8.94	47.77	17.47
	4	16,30	14.40	13.76	7.11	race	5.37	5.14	3.64	8.08	4.31	42.39	17.14	91.59	33.51
	5	26.34	23.29	22.25	11.51		8.69	8.31	5.89	13.06	6.98	68.56	27.72	148.13	54.19
	6	38.64	34.17	32.65	16.88		12.75	12.20	8.64	19.16	10.24	100.57	40.66		79.50
	7	53.19	47.02	44.93	23.23		17.54	16.79	11.89	26.38	14.08		55.97		109.42
	8		61.86	59.11	30.56		23.08	22.08	15.65	34.70	18.54				
					38.87		29.35	28.09	19.90	44 14	23.58				
	9				38.8[illegible]		29.35	28.09	19.90	44.14	23.58				
	10				48.16		36.37	34.80	24.66	54.68	29.21				
	11				58.42		44.12	42.22	29.91		35.43				
	12						52.61	50.32	35.67		42.25				
	13						61.84	59.17	41.92		49.67				
	14								48.68		57.67				
	15								55.94						

the center of the fault. The time duration between the beginning of the transient and the computed time for the ball to pass through the fault compares favorably.

The ringing is present only for a small percentage of the total vibration period. Since most spectrum analyzers give an average amplitude over a period of time, the spectral peak at 22 kHz is not the amplitude of the ring, but an averaged amplitude which is likely to be only a small percentage of the peak time domain amplitude.

A study was performed to determine the transmission of the "ringing" signal through the test rig. An accelerometer was wax-mounted in a number of positions around the rig, and the output was then band-pass filtered between 18 kHz and 25 kHz. It was found that the ringing signal could be detected at all locations on the test rig. Attenuations of approximately 20 dB were experienced for readings taken at positions not on the pedestal holding the faulty bearing. On the pedestal containing the faulty bearing, magnitudes were greatest near the actual fault location.

As a further test, a bar was used to provide a rigid connection between two of the bearing pedestals. At the connected pedestal, the attenuation was reduced to 6 dB. A more rigid structure of this type is representative of the transmission housings encountered in helicopters.

Based on the testing, the appearance of the ring was verified, and it was determined that these vibrations could be transmitted (with some degree of attenuation) to other locations in the structure.

Effects of Loading

The pump and gearing of the test rig were used to help determine the effect of other vibration inputs on the bearing frequencies. Figure 63 shows a spectrum with the pump connected but not operating, while Figure 64 shows a spectrum with the pump in operation.

Data from the spectra show that the operation of the pump affects the low-frequency components of the spectrum but does not affect the high-frequency ring. In lower frequency spectra, the piston pump frequency and its harmonics were quite evident and tended to cover up the ball-pass and race-pass frequencies. The gear mesh frequency was also more evident than the bearing pass frequencies. This finding parallels quite closely the conclusions in the AIDAPS Test Bed analysis. This characteristic was found to be a good generalization for the effect of other signals such as the gear mesh frequency on this phenomenon.

Correlation Functions of the Signal

An autocorrelation function for the test rig signal was plotted for both a good and a bad bearing. Figure 65 shows the autocorrelation for a good bearing, while Figure 66 shows a similar autocorrelation function for a

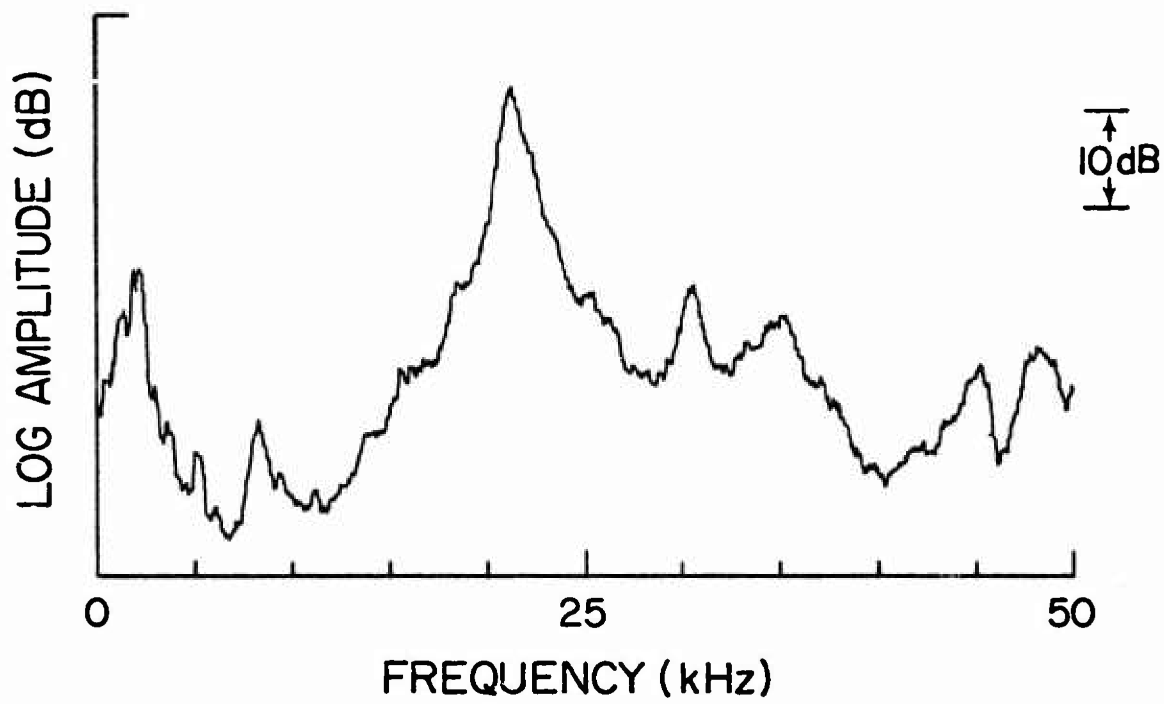


Figure 63. Spectrum with Pump Connected but Not Operating.

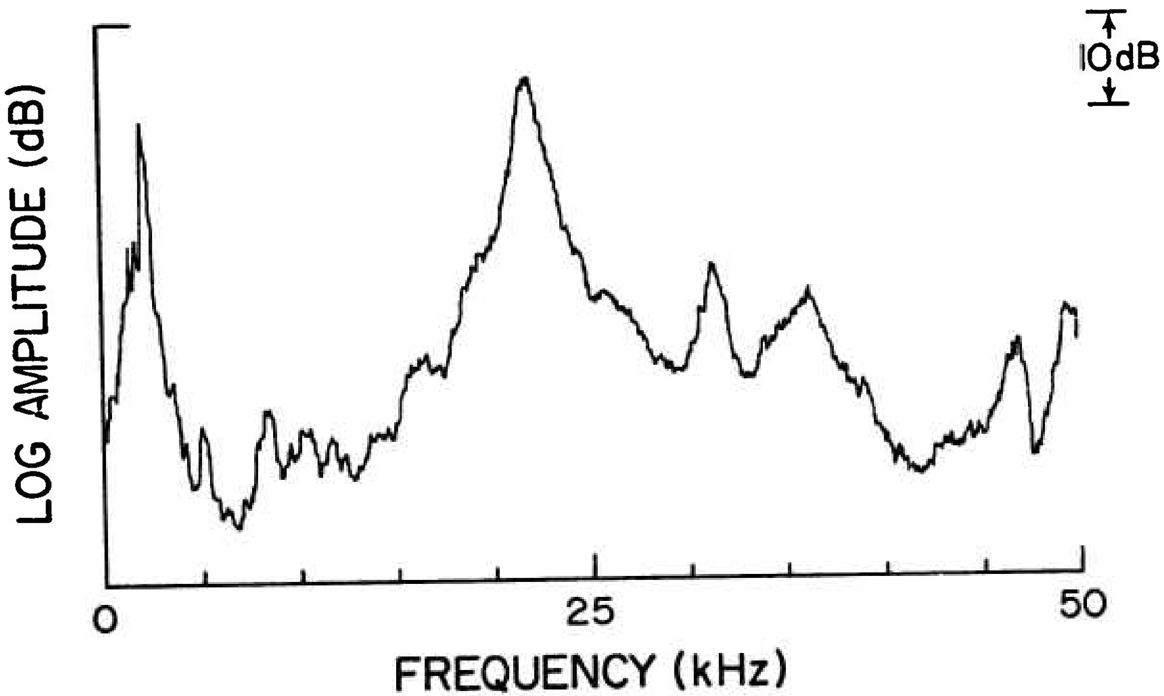


Figure 64. Spectrum for Pump Connected and Operating.

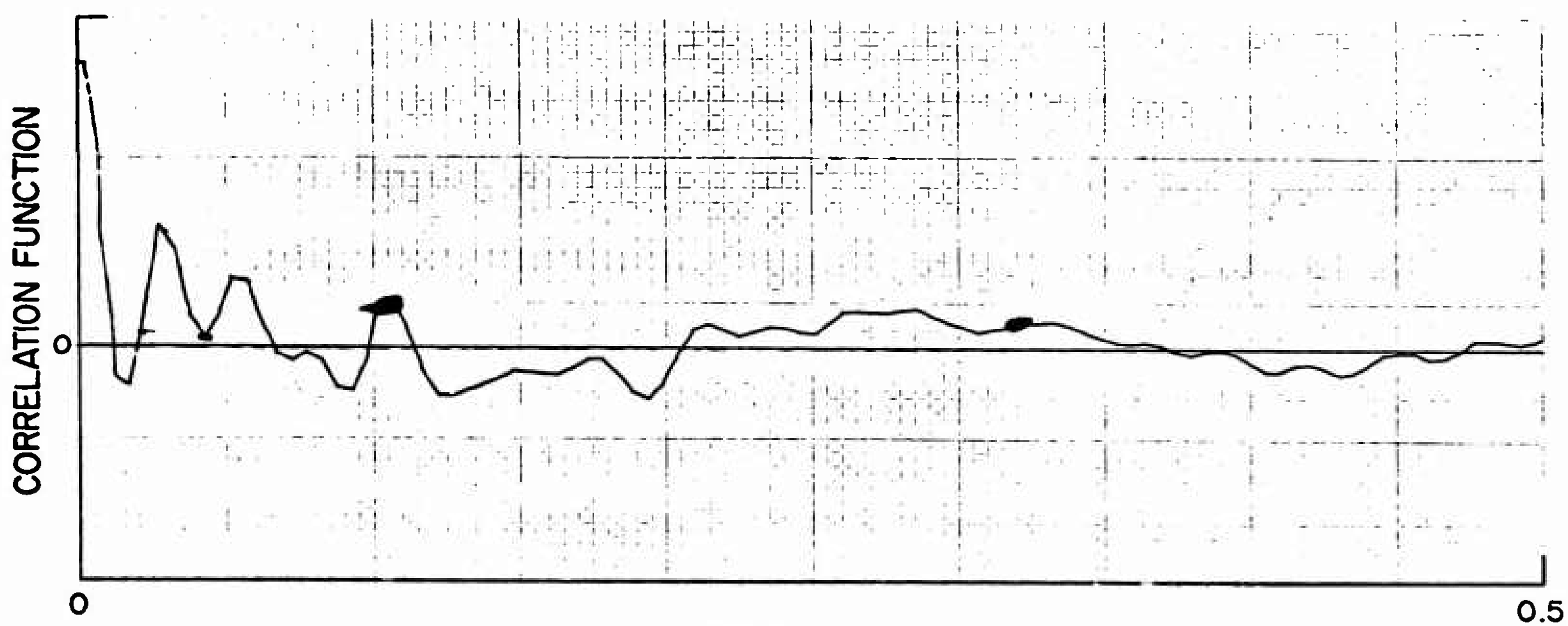


Figure 65. Autocorrelation Function for a Good Bearing.

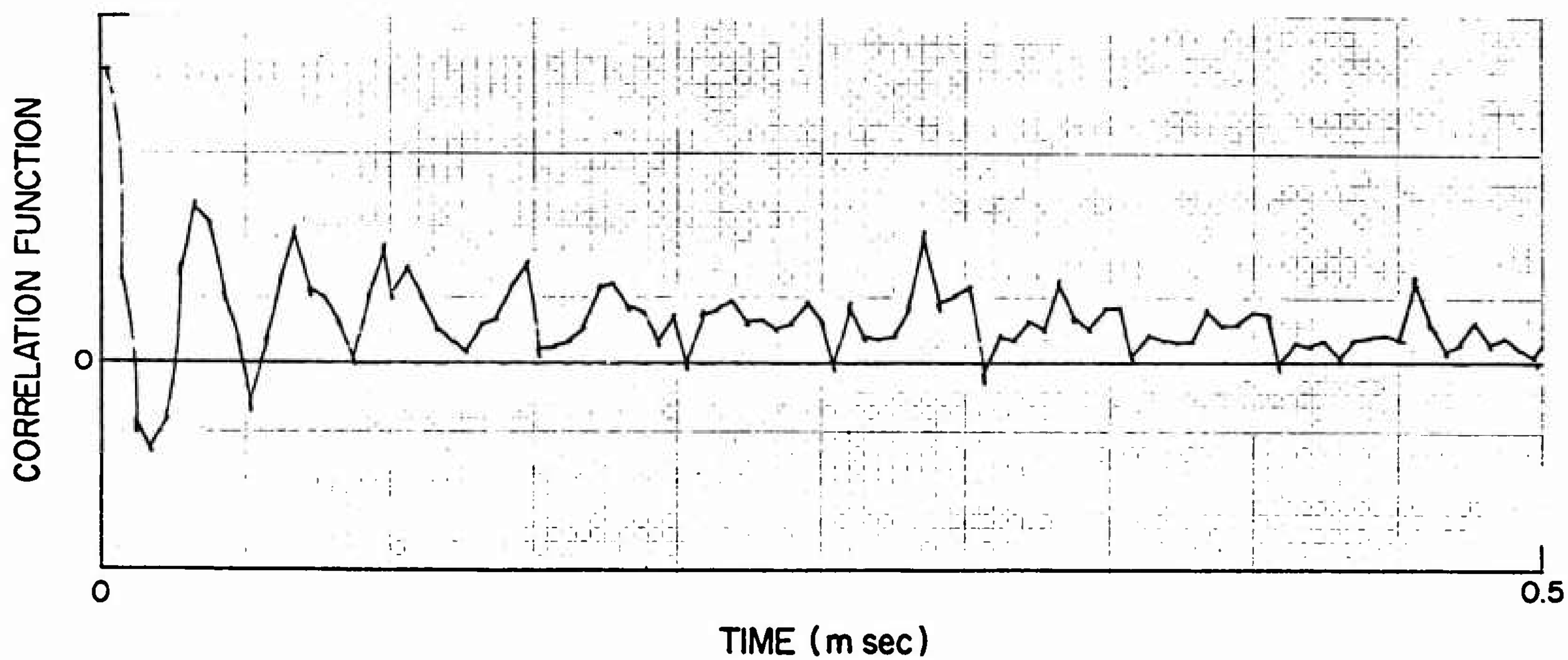


Figure 66. Autocorrelation Function for a Bad Bearing

bad bearing. As may be seen, Figure 66 shows the characteristics of a sinusoidal signal more strongly. This may be caused by the harmonic content present in a signal of a bad bearing.

Probability Density Analysis

Probability density functions were plotted for a good and a bad bearing in Figures 67 and 68. Each of the plots is normalized such that full scale is $\pm$ 4 standard deviations about the mean value. The normal bearing is almost Gaussian, whereas the faulty bearing gives rise to a more non-Gaussian plot which has a larger percentage of the data located near the mean value. The resonant "rings" are present for only a short duration, but they have an effect on the RMS value of the signal.

ANALYSIS VIA MODEL

A simplified analytical model of the bearing rig was developed for use in the evaluation of the various diagnostic techniques. A normal mode simulation technique was used which represented the system for a bad bearing as two second-order systems, the lower of which corresponded to the structural resonance and the other corresponded to the ring frequency. A pulse with a repetition rate corresponding to the frequency associated with the fault position was used to excite the system. To simulate the good bearing, the higher frequency resonance was removed. This action is not altogether realistic since the structural resonance is also excited by the fault. However, observation of testing data showed that the structural resonance was not as sensitive to the fault as the ring frequency. The model was simulated on an analog computer operated in the "rep-op" mode, and the output was tape-recorded and then analyzed.

Figure 69 shows a typical time response of the model, and Figure 70 depicts a typical frequency spectrum for a bad bearing. The series of spikes which may be noted in the spectrum are caused by the "rep-op" operation of the computer and correspond to the impulse response as was observed in spectra produced for the test rig. For this reason the 22-kHz ring is not discrete, but quite broad, when observed in the frequency domain.

Cross-Correlation With Test Rig

A cross-correlation of the model results with the signals produced by the test rig was attempted. Even though the time plots looked quite similar and the spectra were related, the results obtained were not intelligible. These results may be explained by the slight speed variations which occur during the operation of the test rig. Such speed variations can ruin a cross-correlation analysis. Such a speed variation is to be expected in most physical systems. Cross-correlation, with any signal obtained from an operating physical system, will prove to be difficult unless quite sophisticated pre-processing is used.

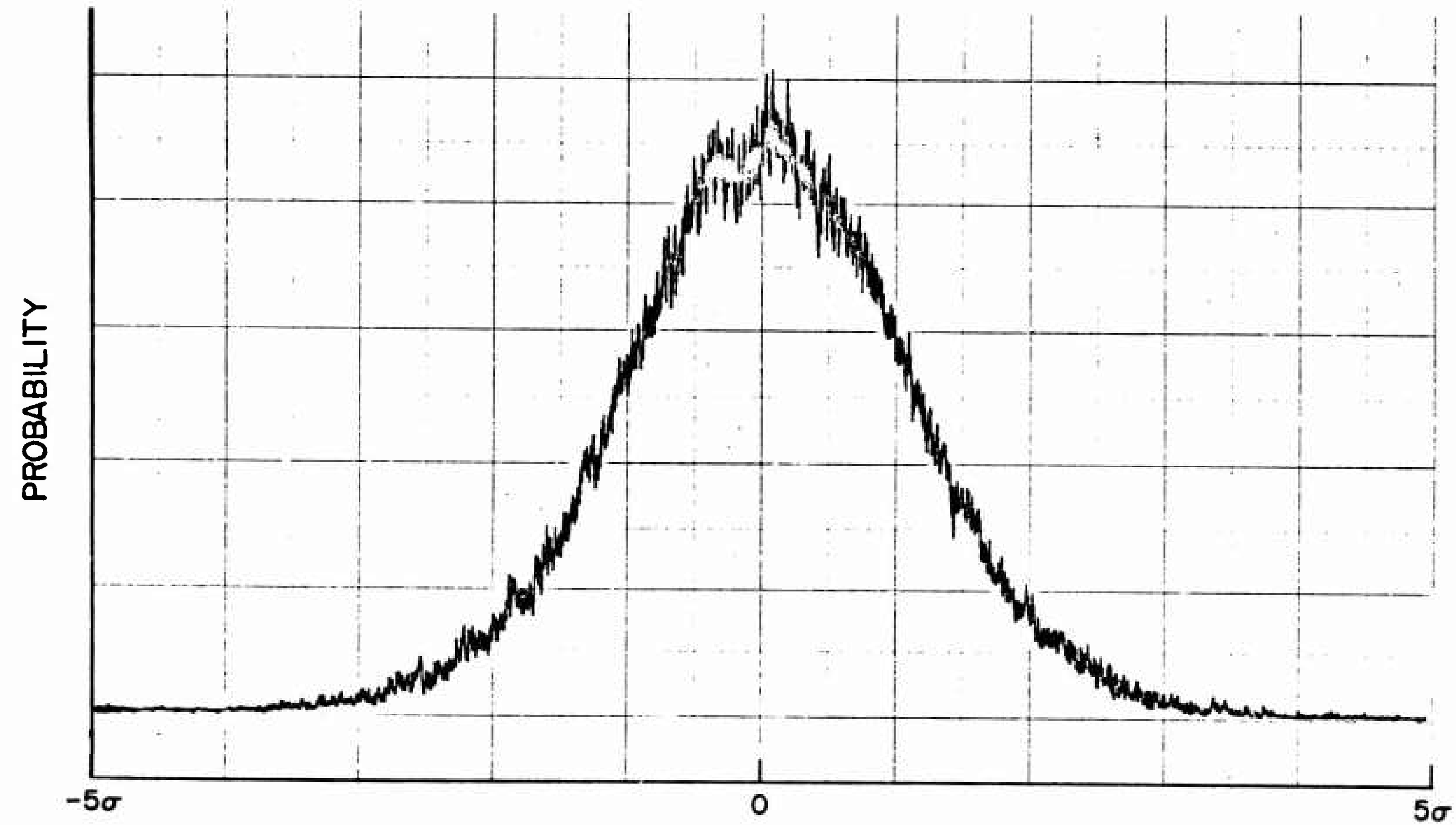


Figure 67. Probability Density Function for a Good Bearing.

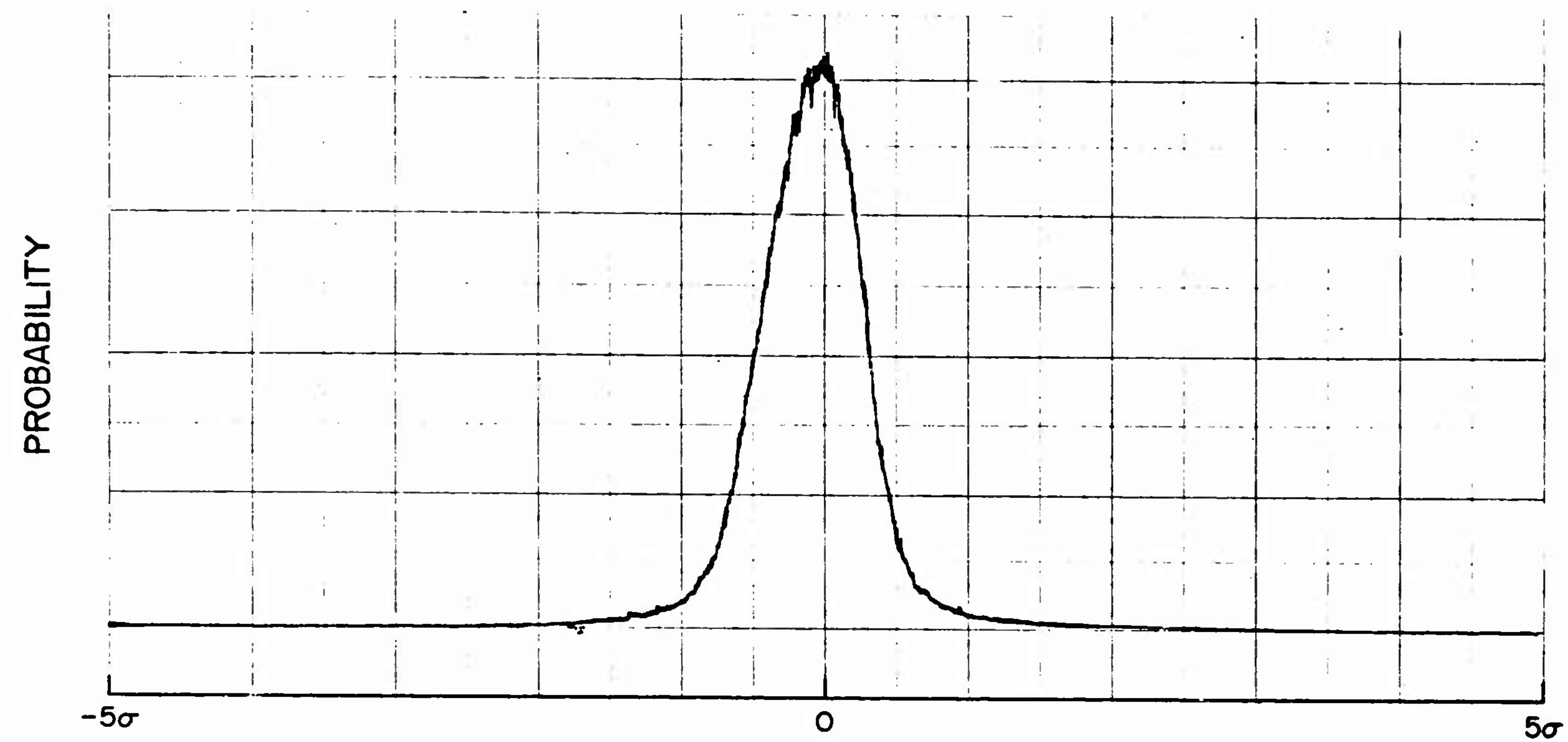


Figure 68. Probability Density Function for a Bad Bearing.

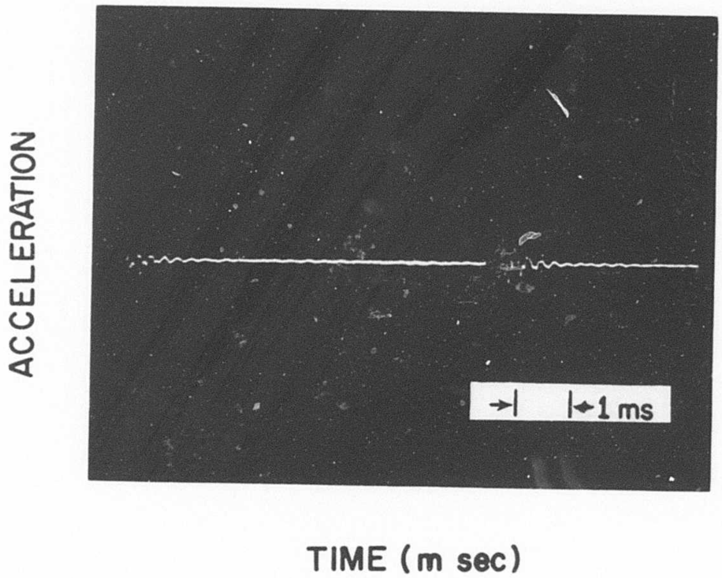


Figure 69. Time Trace of Model Response.

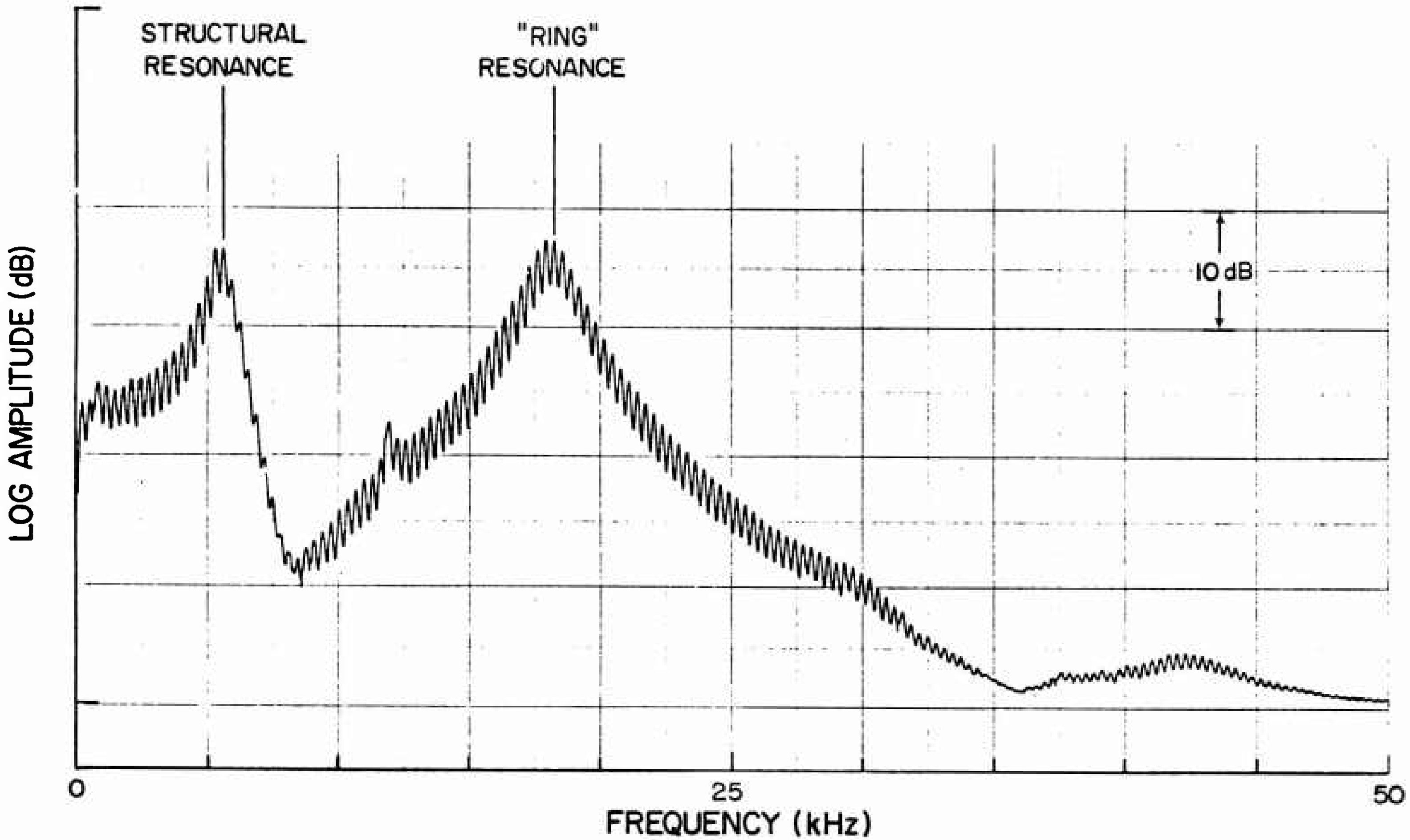


Figure 70. Typical Spectrum for Model.

Correlation Function of Model

An autocorrelation of the good signal is shown in Figure 71, while Figure 72 shows an autocorrelation function of the bad signal; Figure 73 shows a cross-correlation between the two. As noted with the other data, more peaks are noted with the bad signal due to the higher harmonic content. The cross-correlation shows the strongest component at the period of the good signal. The cross-correlation was easily calculable in this case, since the manner in which the two signals were produced made accurate synchronization possible.

Signal-to-Noise Analysis

A set of experiments was performed using the model to determine the effect of varying signal-to-noise ratios (S/N) on the various analysis procedures. Signal-to-noise ratio in this context was computed by taking the ratio of the peak ring amplitude to the rms level of the noise. The procedures considered were spectral analysis via the swept-frequency analyzer and the real-time analyzer with averaging, autocorrelation, probability density functions, and impact index calculations.

Figures 74 through 77 show spectra produced by the swept-frequency analyzer for S/N of 2.0, 1.0, 0.5, and 0.1, respectively. As can be seen, the information in the spectrum is lost as the signal-to-noise ratio decreases. The statement is often made that averaging with a real-time analyzer can eliminate problems associated with signals buried in noise. This is true for a limited range of conditions. Figures 78 and 79 show spectra produced by a real-time analyzer for S/N = 1.0. In Figure 78 a single spectrum is shown, while Figure 79 shows the results of 64 averages. The results seen in Figure 79 show an improvement in this case, but if the signal-to-noise ratio decreases, the averaging produces no improvement and the same effect as observed with the swept-frequency analyzer occurs.

The effects of varying S/N on the autocorrelation function are shown in Figures 80 through 82. The function is not quite as "smooth" as the ratio decrease, but the essential results are unchanged.

Figures 83 through 85 show the effects of S/N on the probability density function. As can be seen, the increase of noise levels causes the plot to flatten and become more Gaussian.

Table VII shows the values of the impact index as calculated for different signal-to-noise ratios. A decrease in the S/N destroys the effectiveness of this analysis procedure.

The conclusion which may be drawn from this set of experiments is that most analysis procedures run into difficulty unless some consideration and processing are used to increase signal-to-noise ratios. The only analysis procedure which appears relatively unaffected is correlation. Another available procedure which can also overcome this problem is time averaging.

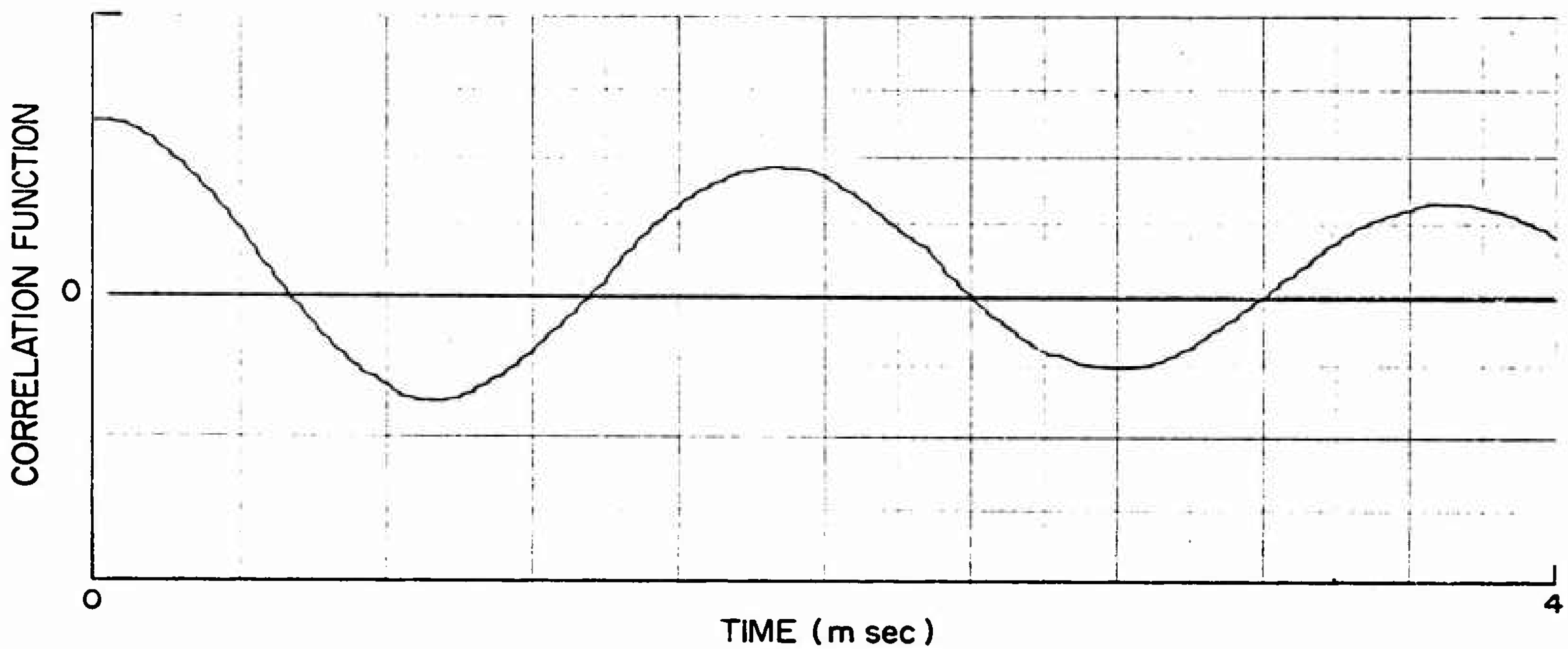


Figure 71. Autocorrelation of Good Signals.

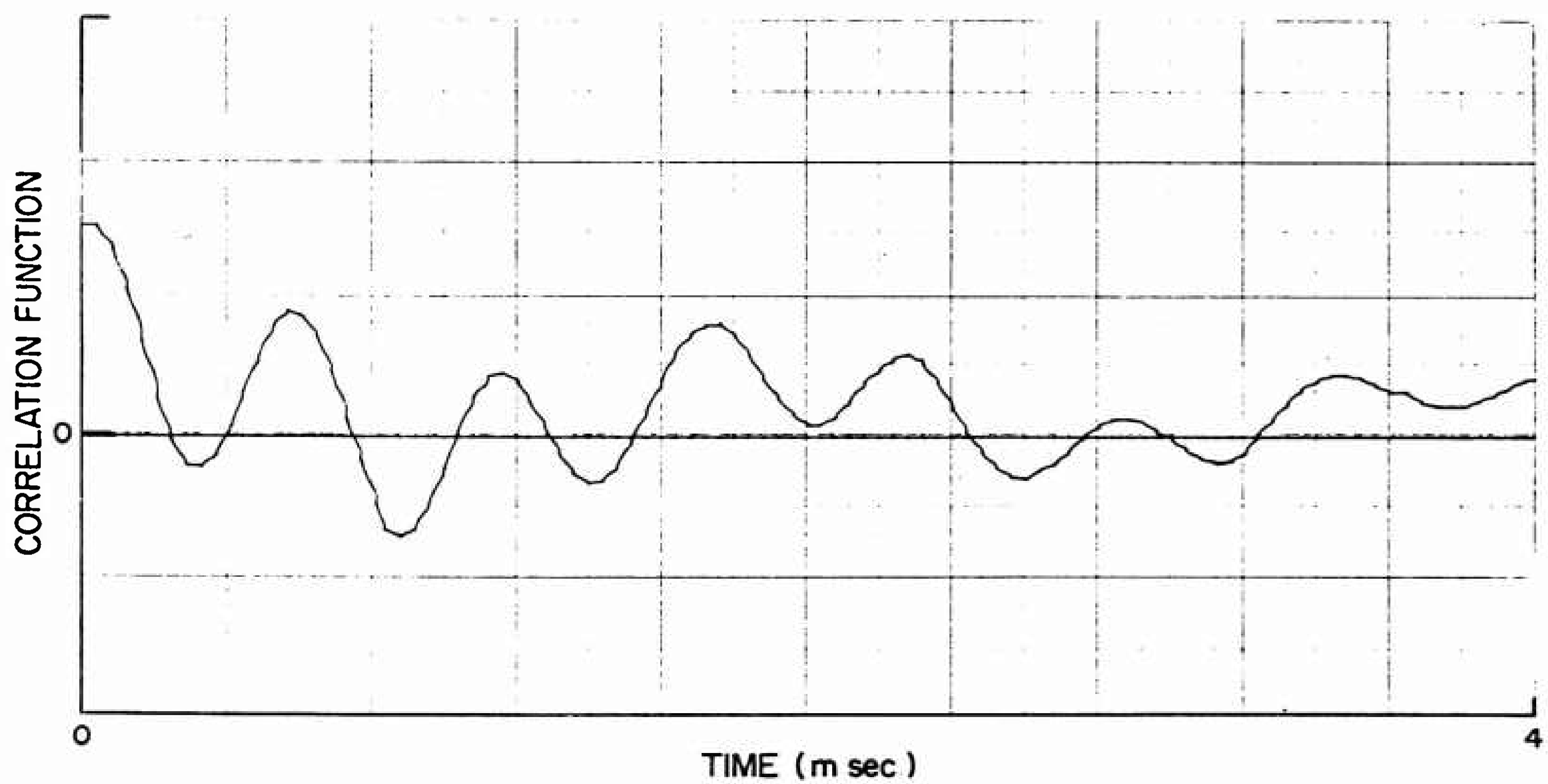


Figure 72. Autocorrelation of Bad Signals.

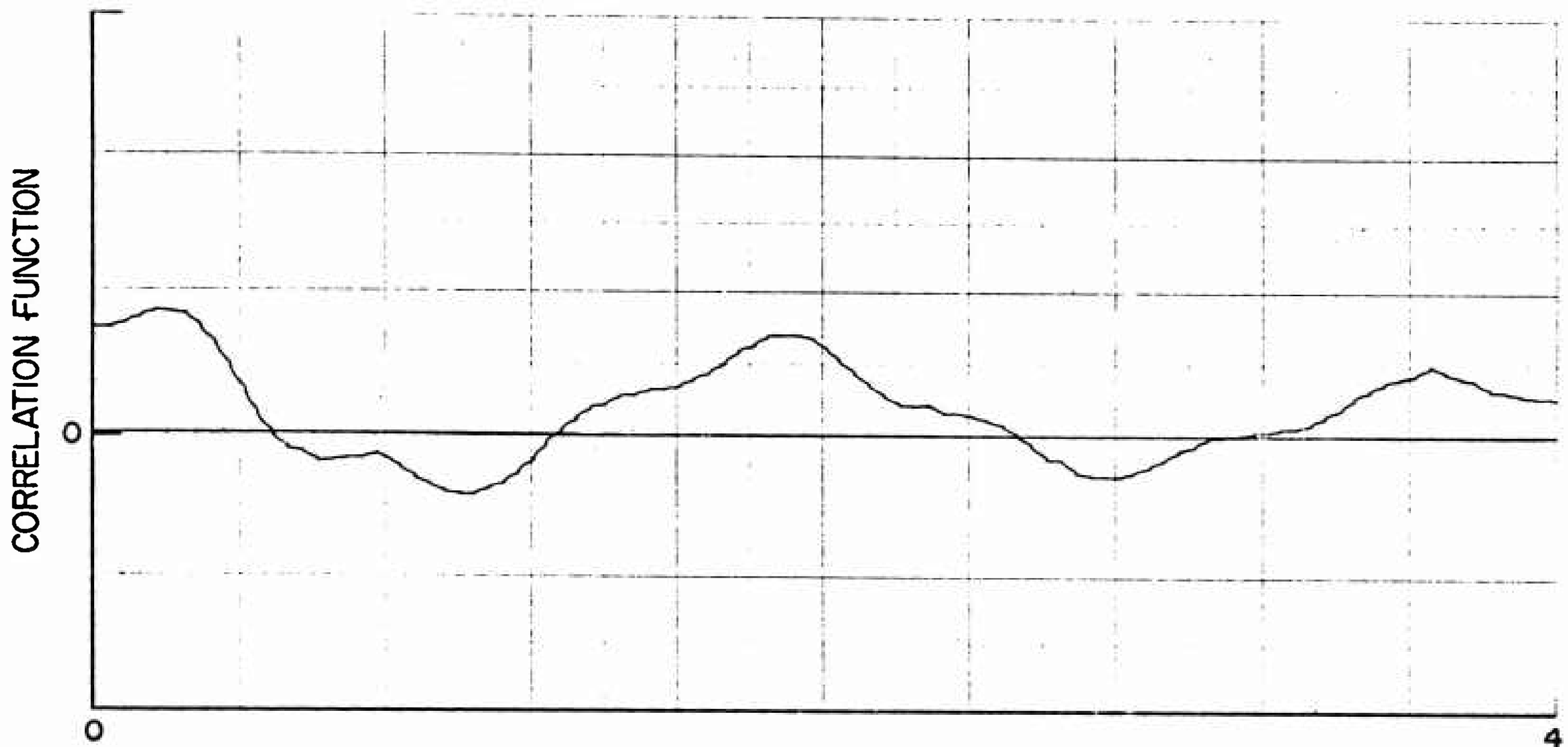


Figure 73. Cross-Correlation of Good and Bad Signals.

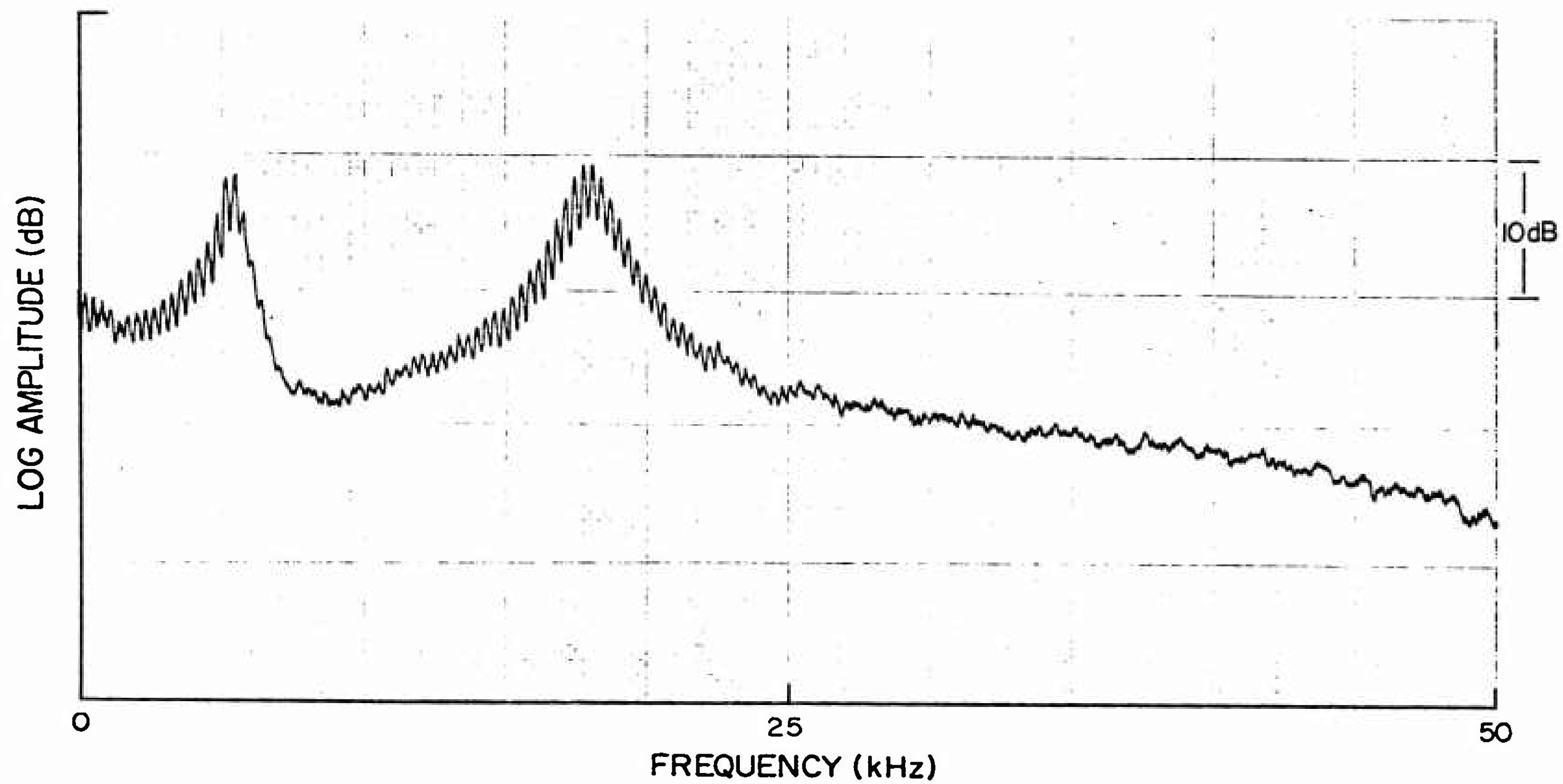


Figure 74. Spectrum with S/N = 2.0.

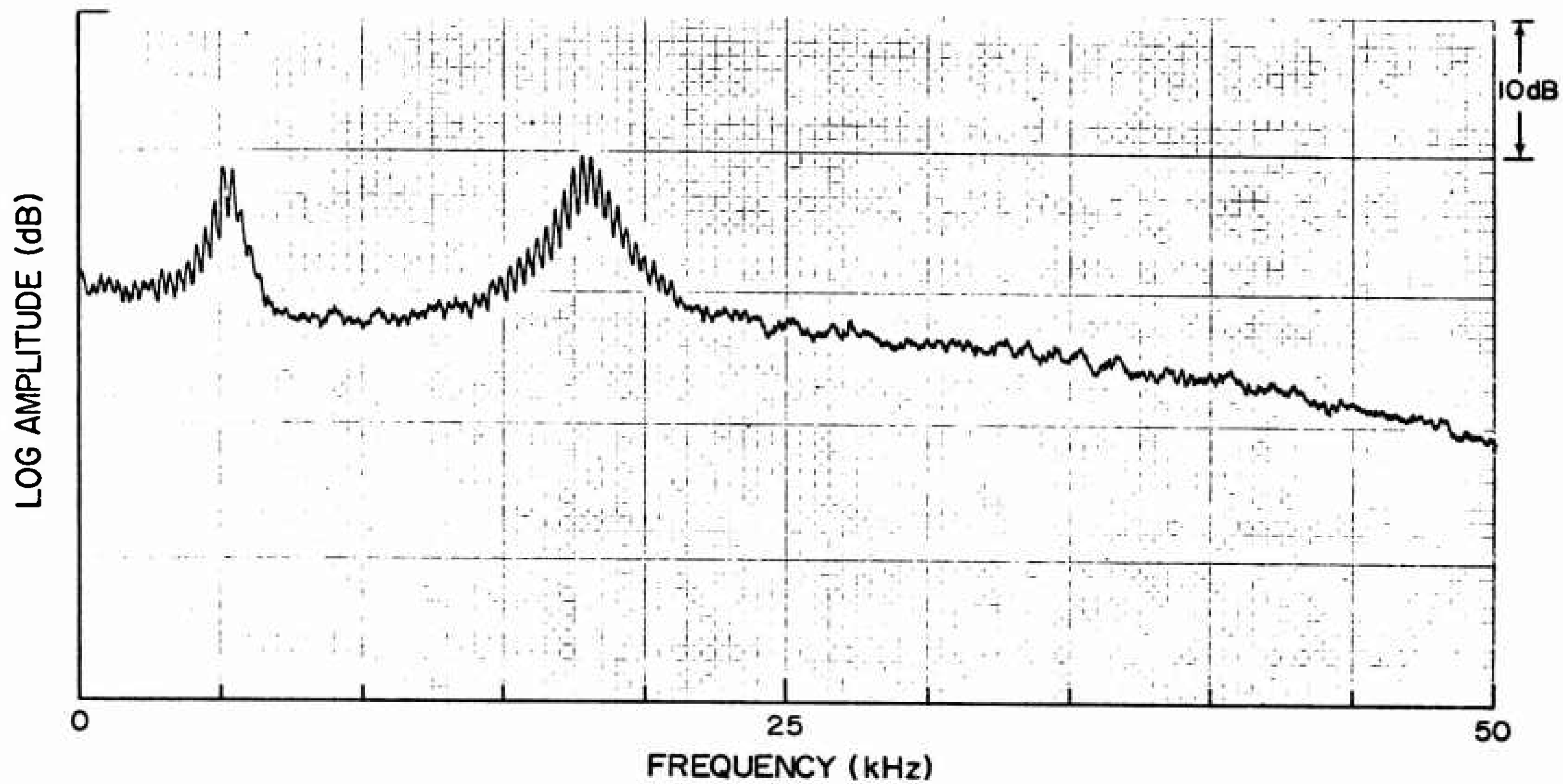


Figure 75. Spectrum with $S/N = 1.0$.

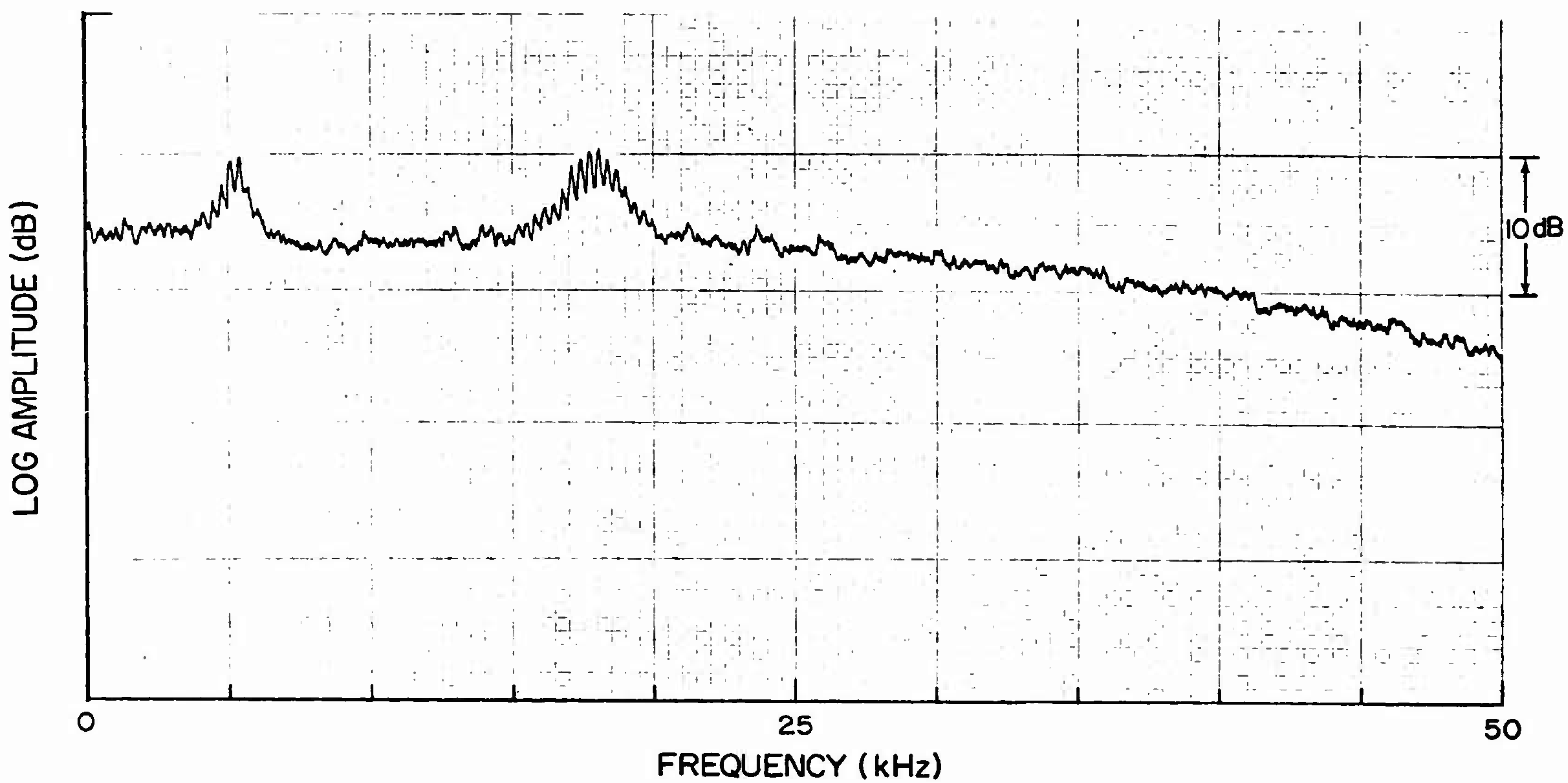


Figure 76. Spectrum with S/N = 0.5.

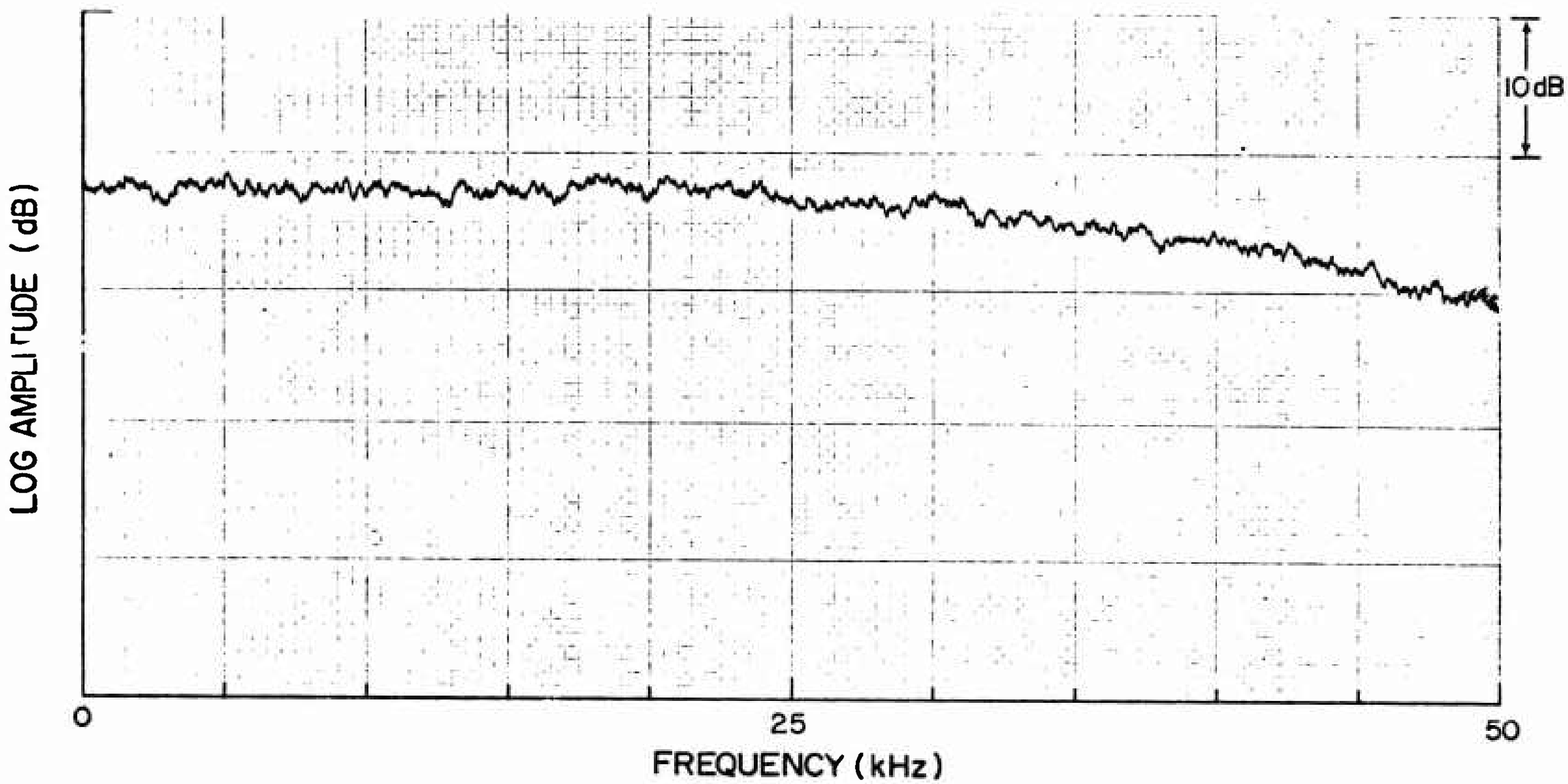


Figure 77. Spectrum with S/N = 0.1.

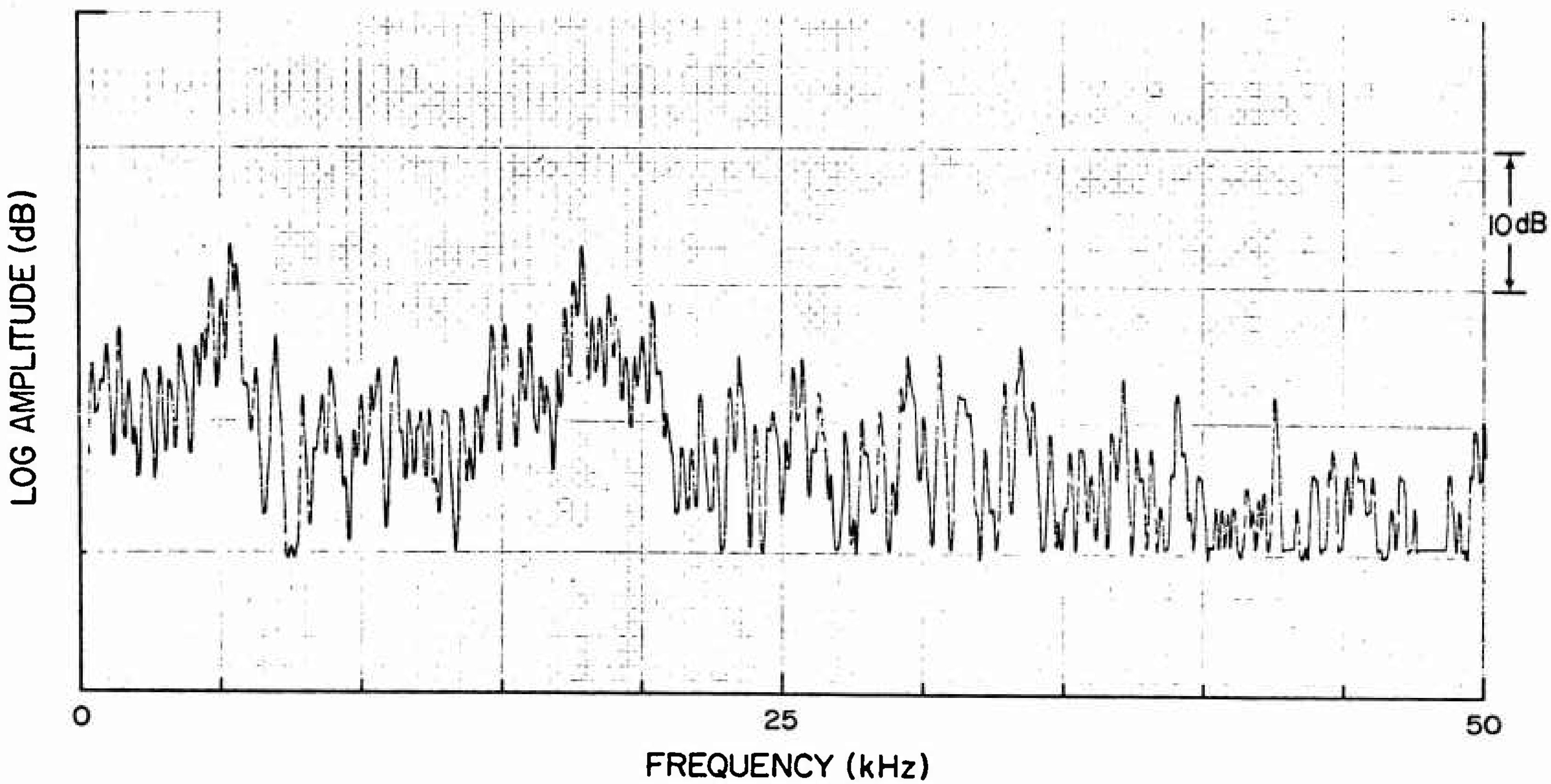


Figure 78. Spectrum from Real-Time Analyzer (Single Average)

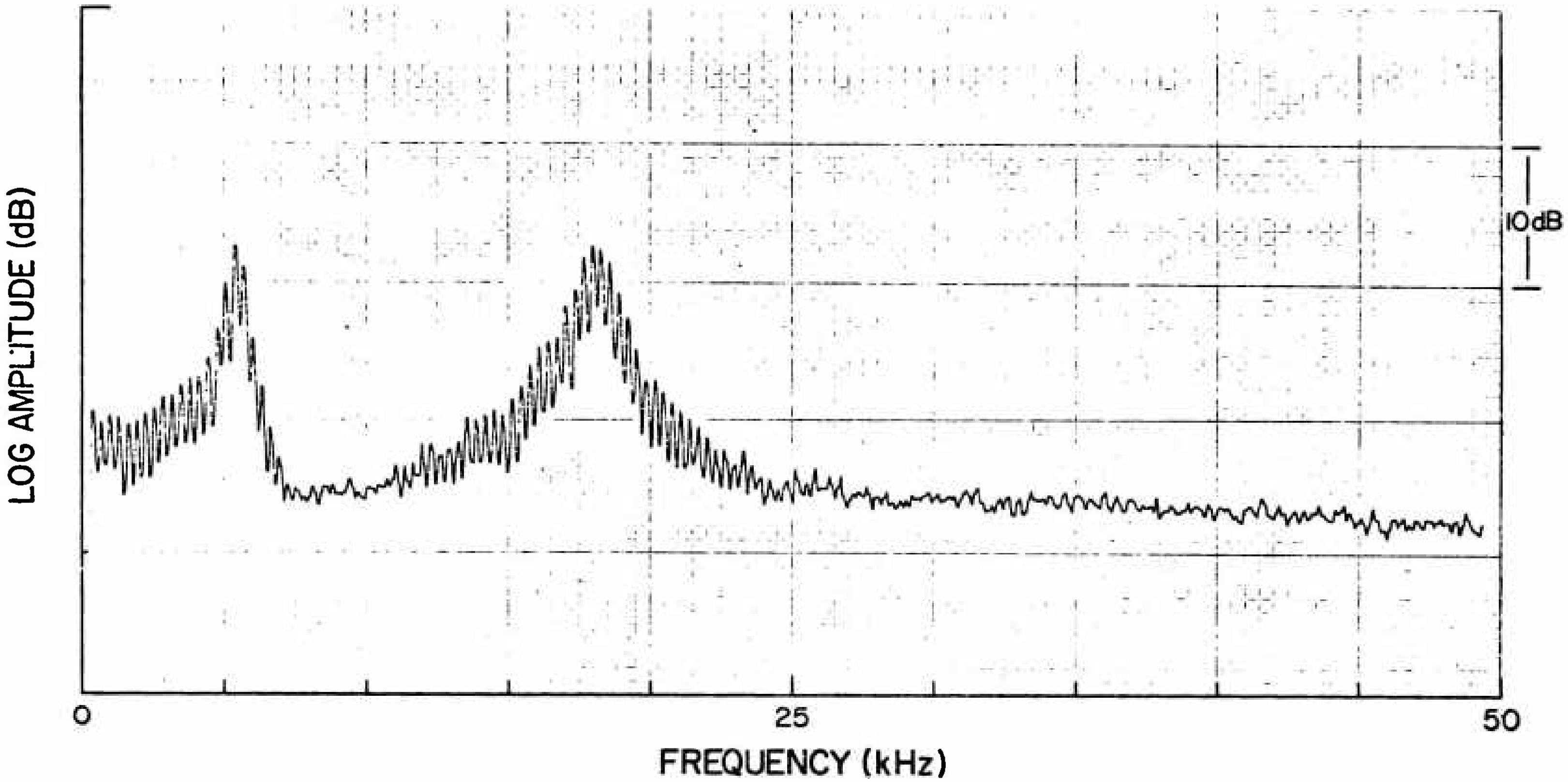


Figure 79. Spectrum from Real-Time Analyzer (64 Averages).

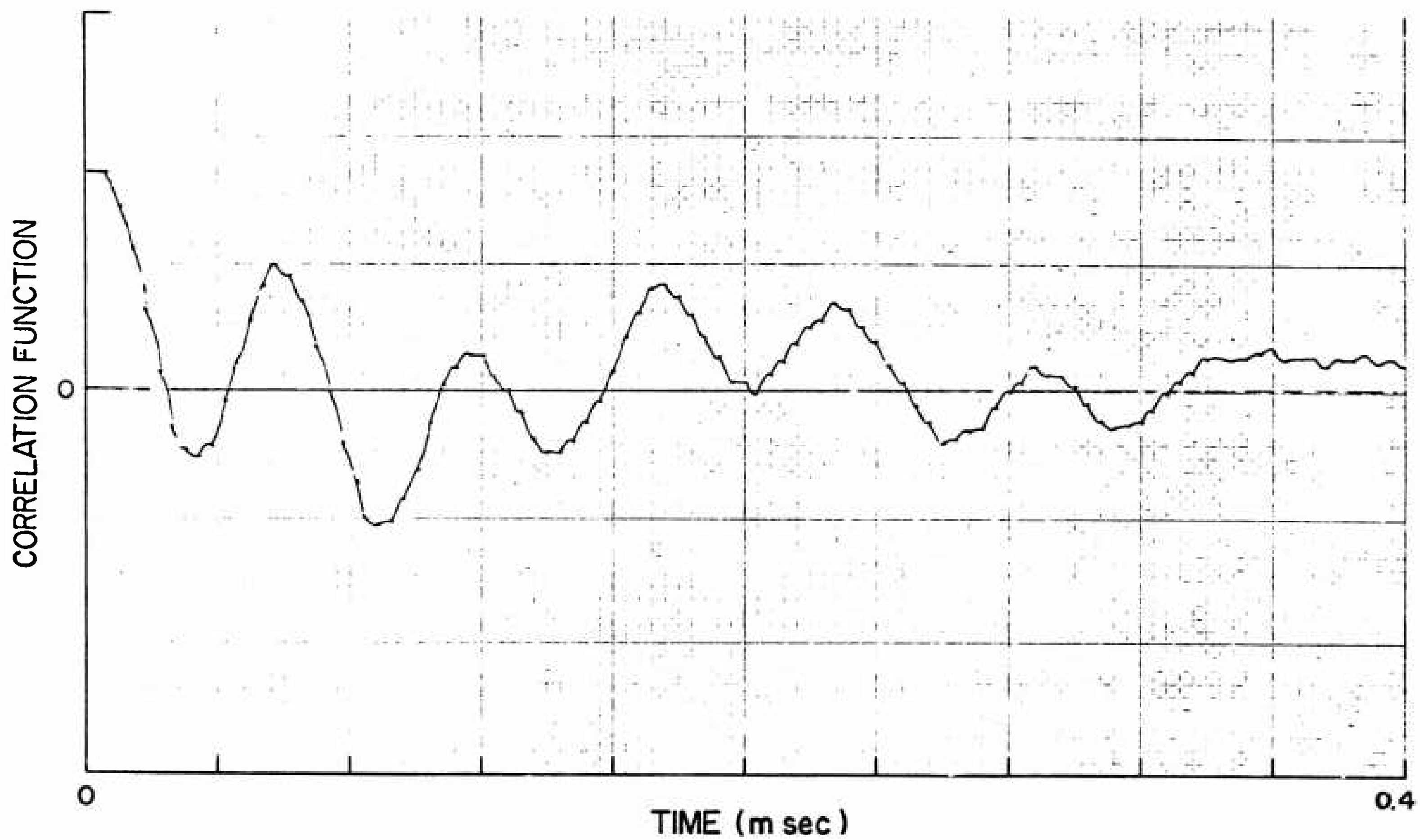


Figure 80. Autocorrelation with S/N = 2.0.

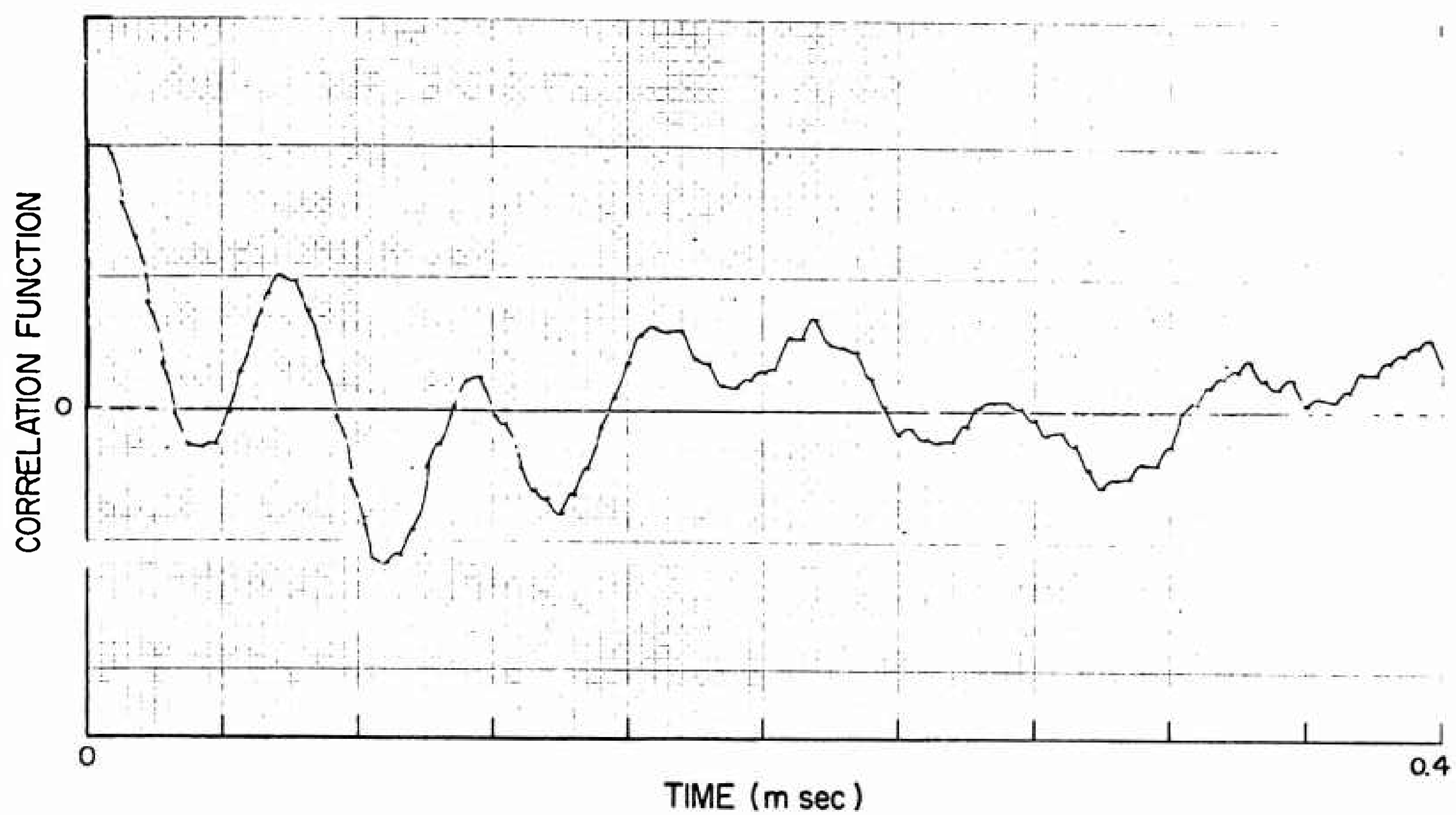


Figure 81. Autocorrelation with S/N = 1.0.

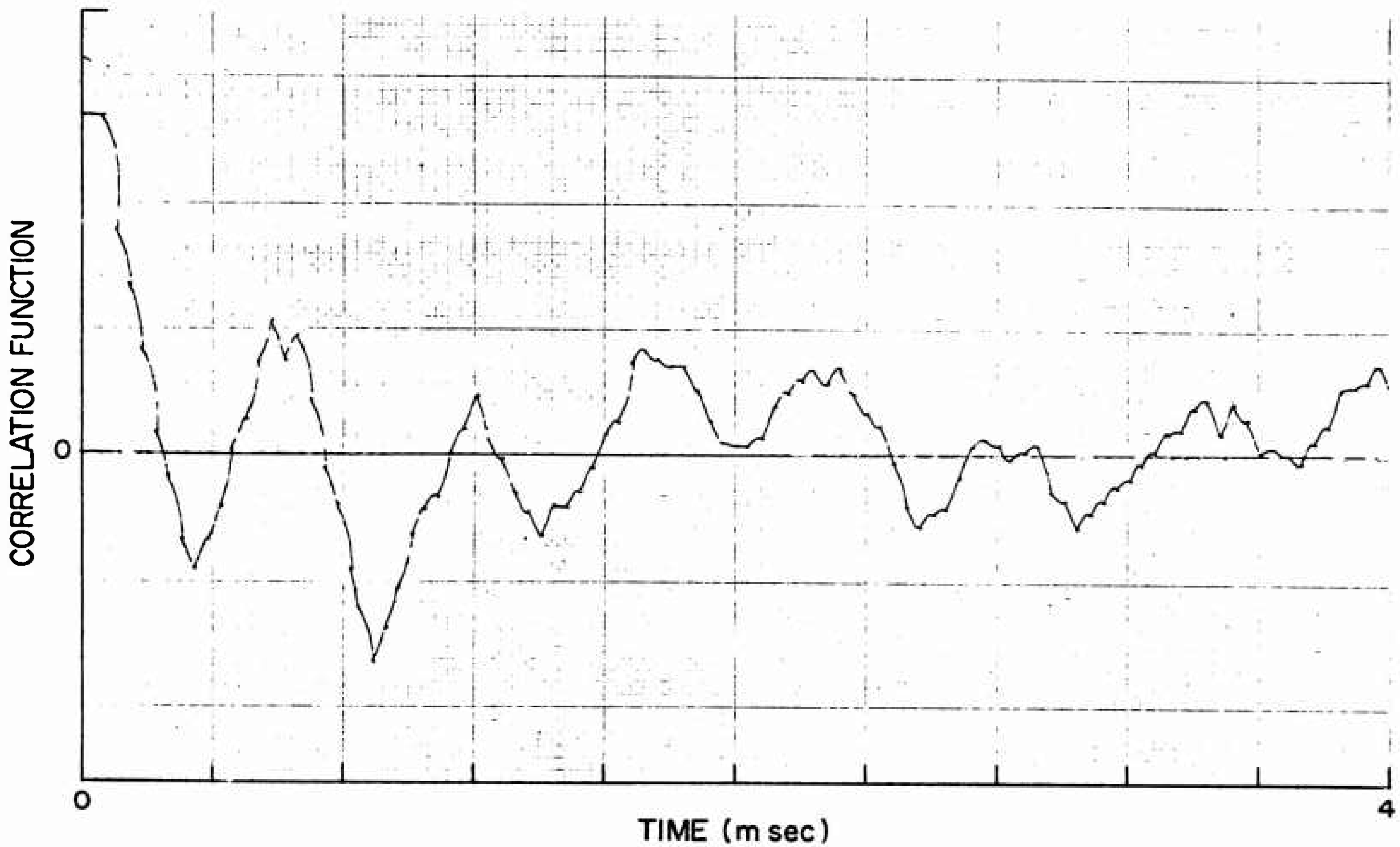


Figure 82. Autocorrelation with S/N = 0.5.

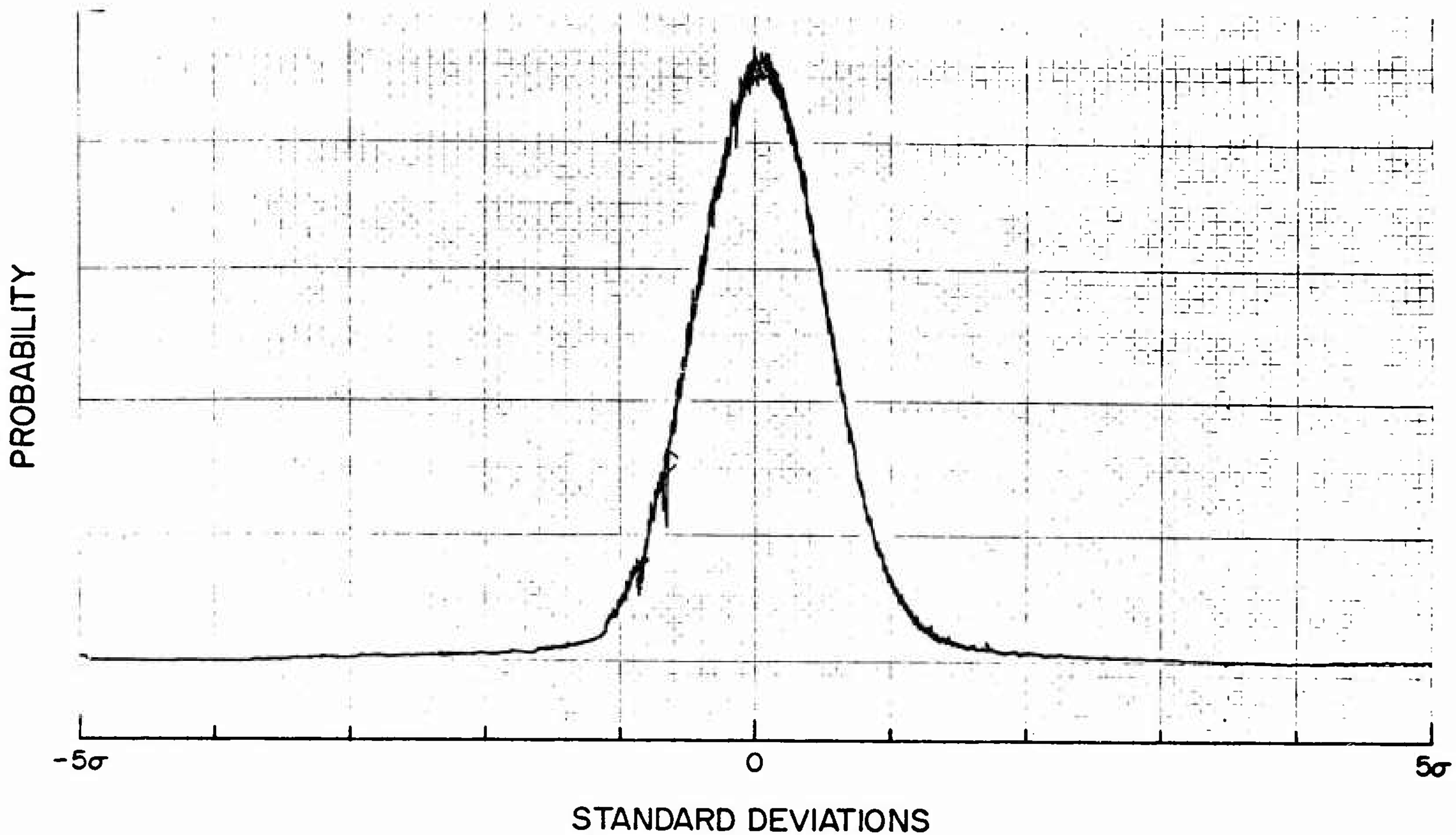


Figure 83. Probability Density Function with S/N = 2.0.

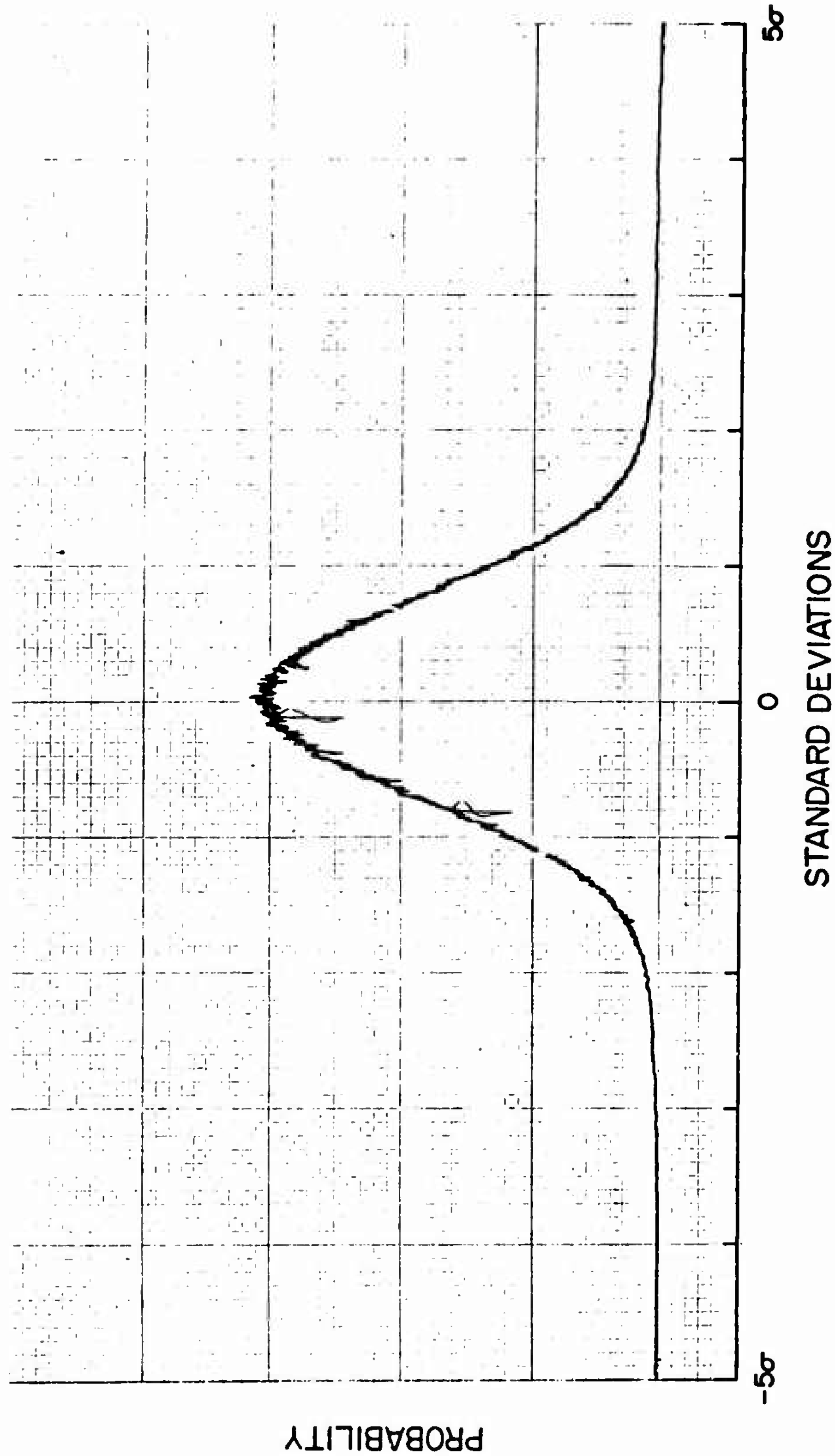


Figure 84. Probability Density Function with S/N = 1.0.

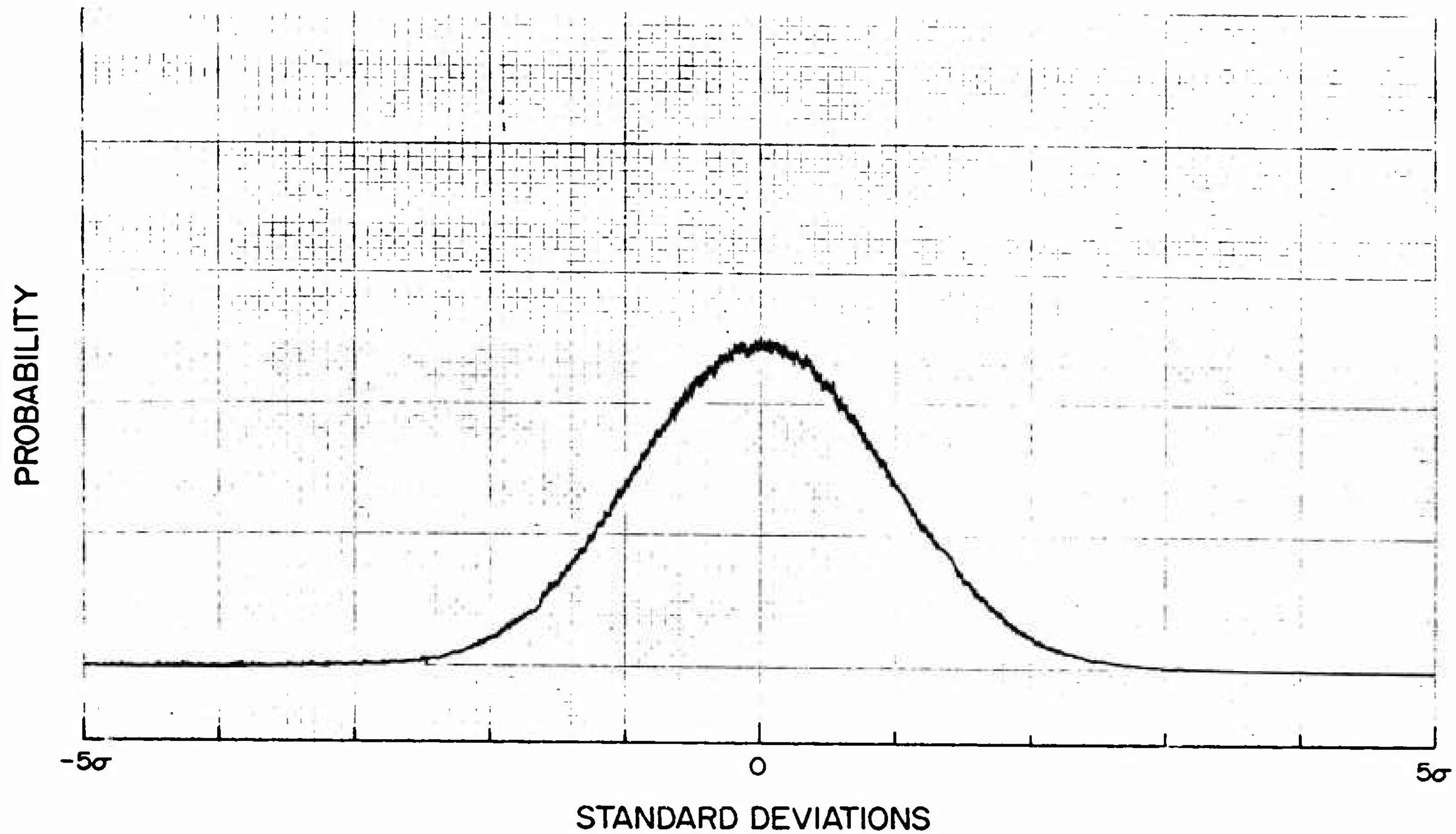


Figure 85. Probability Density Function with S/N = 0.5.

TABLE VII. EFFECT OF SIGNAL-TO-NOISE RATIO ON IMPACT INDEX	
S/N	Impact Index
2.0	4.25
1.0	3.49
0.5	2.56
0.1	1.86

STRESS WAVE ANALYSIS

Some experimentation was performed to study the stress wave phenomenon as utilized by SKF in their shock pulse analyzer. The study was performed on a 20-inch longitudinal bar to get a qualitative understanding of the phenomenon which could then be extrapolated to a mounted bearing. The longitudinal rod is also of interest since it is the classical example used in most books to explain the stress wave phenomenon. References 73 and 74 give a detailed description on this phenomenon.

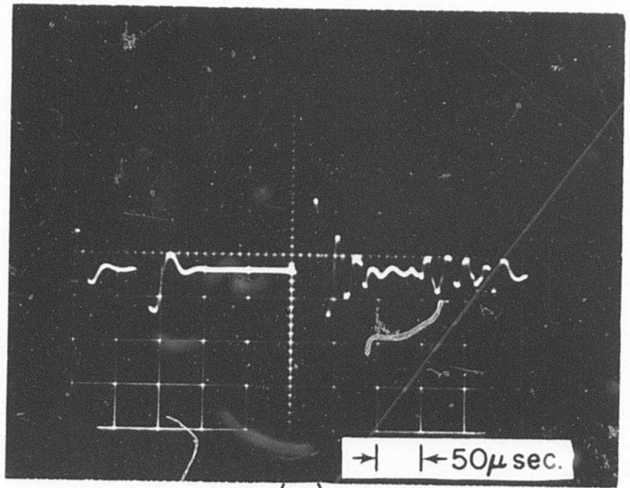
The tests were performed in the following manner. A bearing was wax-mounted to one end of a bar, the other end of the bar was impacted, the accelerometer signal was high-pass filtered, and the results were photographed with an oscilloscope camera. As this experiment was directed at the type of analysis performed by SKF, the filter was set to pass the accelerometer resonant frequency.

Figure 86 shows the results from three accelerometers: an Endevco 2215 with a resonance of 35 kHz, a Bruel and Kjaer 4335 with a resonance of 45 kHz, and a Bruel and Kjaer 4344 with a resonance of 118 kHz. As can be seen, the accelerometers may be "rung" at their resonances by an impact. The Bruel and Kjaer accelerometers were the easiest to excite into a free resonant mode.

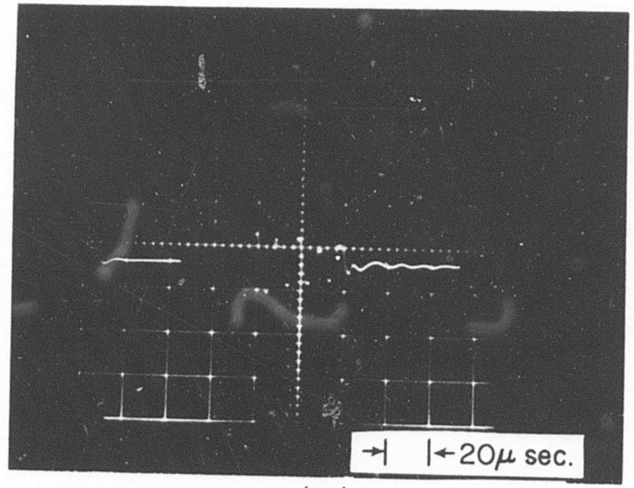
A further test was performed to determine the effect of interfaces on the amplitude of the response. First one and then two rod extensions were bolted between the accelerometer and the impact point. Figure 87 shows the results of this experiment. An attenuation of approximately 6 dB per interface was found. This was substantially less than the 14 dB per interface quoted by SKF. The difference in these results may be explained since the interface provided here was very solid and straight, whereas interfaces referred to by SKF may not have been as rigid.

All accelerometers rang at their unmounted natural frequency. In the high-frequency (B & K 4344) accelerometer, the mounted natural frequency is quoted at 70 kHz, but this frequency did not appear in this test.

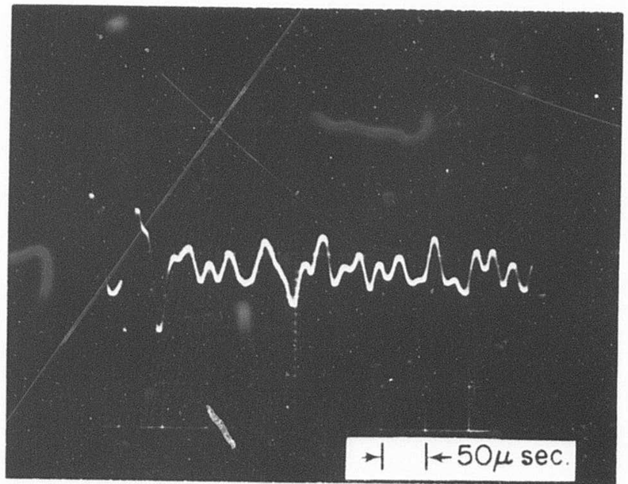
The accelerometers were next placed on the bearing test rig and again band-pass filtered at their resonant frequencies. It was found that the resonant



(a)



(b)

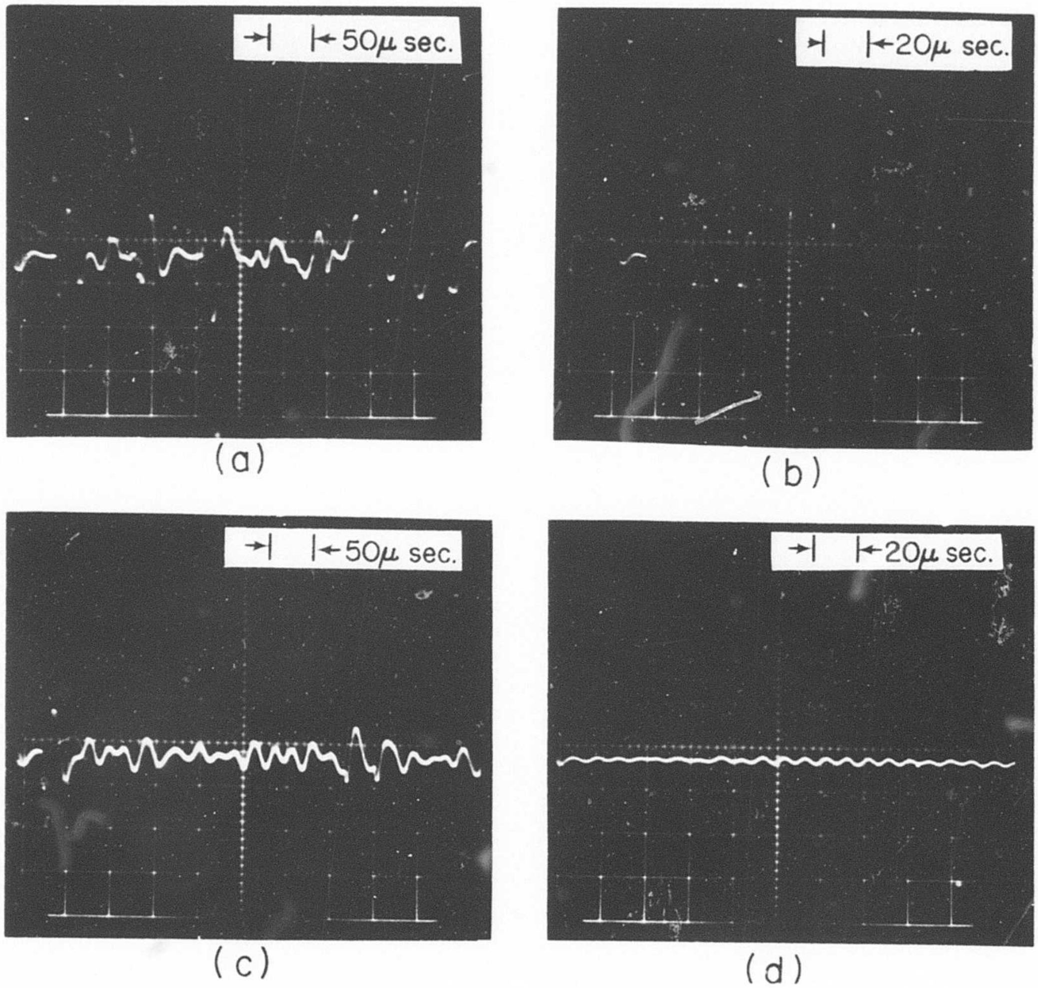


(c)

Vertical Scale: Acceleration
Horizontal Scale: Time (msec)

Fig. (a) B&K Accelerometer Mounted on Bar; Filtered at 30 kHz, f = 45,000 Hz
(b) B&K 118-kHz Accelerometer Mounted on Bar; Filtered at 90 kHz, f = 112,500 Hz
(c) Endevco Accelerometer Mounted on Bar; Filtered at 20 kHz, f = 40,000 Hz

Figure 86. "Ringing" of Varicus Accelerometers.



Vertical Scale: Acceleration
Horizontal Scale: Time (msec)

Fig. (a) B&K 47-kHz Accelerometer Mounted on Bar with Extension Filtered at 30 kHz, f = 45,000 Hz
(b) B&K 118-kHz Accelerometer Mounted on Bar with Extension Filtered at 90 kHz, f = 104,200 Hz
(c) B&K 47-kHz Accelerometer Mounted on Bar with Two Extensions Filtered at 30 kHz, f = 45,000 Hz
(d) B&K 118-kHz Accelerometer Mounted on Bar with Two Extensions Filtered at 90 kHz, f = 104,200 Hz

Figure 87. "Ringing" of Accelerometers with Interface Added.

frequency could be observed even though it was very low in amplitude (approximately 40 to 60 dB below the signal level). Frequency spectra were plotted for the bad bearings with the Bruel and Kjaer 4335 and Endevco 2215 accelerometers. Additional peaks were observed in the frequency spectrum, one of which might be construed to be the resonant frequency of the accelerometer. It was also noted that the larger accelerometers tended to mass load the structure, thus further altering the higher frequency spectra. Mass loading could be very likely in any structure where high-frequency resonances are being monitored.

One final difficulty, which could occur with the shock pulse technique and has not been previously mentioned, is the possibility that one of the high-frequency structural resonances could fall very close to the accelerometer resonance. If this should happen, the shock pulse readings could be very erroneous.

DISCUSSION OF EXPERIMENTAL RESULTS

Much data and general information have been presented here. A short listing of the major points would show:

1. The data presently available for helicopters has been detailed.
2. Actual helicopter signals are strongly affected by the gear mesh frequencies and, therefore, make time domain techniques difficult to implement.
3. The helicopter data show distinct variations due both to helicopter mode of operation and to transducer placement.
4. Analysis of the available data by powerful pattern recognition techniques can produce significant results.
5. The high-frequency "ringing" phenomenon is one of general occurrence in bearings and is not contaminated by extraneous signals in the data.
6. The high-frequency signal transmits through the machine from its point of origin.
7. Difficulties are encountered in cross-correlating data with other signals being produced by a rotating machine.
8. Decreased signal-to-noise ratios will adversely affect most analysis procedures.
9. Shock waves in a continuum may be used to "ring" an accelerometer.

As may be noticed, there is a good deal of work that has been performed

on the high-frequency bearing techniques. One of the primary reasons for this was the lack of any other available information on the high-frequency bearing signals. This information had to be produced to properly evaluate the techniques utilizing the phenomenon.

GENERAL CONCLUSIONS

In this section, the generalized diagnostics problem in helicopters is discussed. The discussion is broken down into the types of techniques, i.e., mechanically related vs. pattern recognition, gear vs. bearing detection, time domain vs. statistical vs. frequency domain, etc.

TECHNIQUE TYPE

Two broad classes of diagnostic techniques have been discussed. The first class, those designed on the basis of mechanical phenomena, requires the modeling of the phenomena related to specific failure modes to be performed. The second class, pattern recognition, is performed on a purely statistical basis and requires a great deal of data from transmissions containing both faulty and good parts. It might often be the case that the discriminants developed from either of these methods would be similar. However, the discriminant detection level would be selected from a mechanical model in one instance and statistical confidence analysis in the other.

It is the opinion of the authors and of many other knowledgeable individuals active in the diagnostics field that the mechanical modeling approaches are favored over the pattern recognition schemes. In fact, some of the pattern recognition advocates readily admit that the more information that is available about mechanical phenomena, the better off a pattern recognition scheme will be.

A primary reason that pattern recognition is often used is that when asked to produce a usable diagnostic system under limited time constraints, the easiest approach is to statistically determine differences in good and bad part data. This works well as long as there are very few failure modes being detected. However, as the list of possible failure modes and numbers of parts increases, it becomes necessary to run several samples of each failure mode in order to assure the statistical reliability of the technique. The total number of required tests could then become extremely large and, since implantation data is not easy to obtain, extremely expensive. If all of these tests are not run, a new failure mode which had not been previously programmed into the system might go undetected in later use of the technique. The number of parameters or discriminants required for detection is likely to increase as the number of failure modes increases. The ability to detect failures on an LRU basis with only one or a few parameters (as done by Northrop or Scope) is also doubtful, since each failure mode will not excite the structure in the same manner. If there should be a situation where each failure mode did do this, there is a strong likelihood that mathematical modeling would predict the same phenomenon.

While the mathematical modeling approach requires that more effort be expended prior to acquiring actual data, it guarantees that discriminants are physically related to the failure mode being detected. By having this predetermined physical knowledge, the extent of full-scale failure mode

testing for a given discriminant is substantially less than that required for pattern recognition. To be successful, a model must consider such things as noise saturation effects and the effects of other component frequencies. Modeling has the power of predicting the effect on vibration signatures of multiple failure modes.

One difficulty with modeling is that most models of gears and bearings have been quite qualitative in nature. The General Electric Research and Development Laboratory has been one of the leading proponents of dynamic modeling of failure modes. Their efforts have been aimed primarily at rolling element bearings and gears. Very little of their modeling work has been published, so it is difficult to ascertain how detailed their efforts have been. However, from the types of analyses they perform after establishing a model, it would seem that they look for specific data trends and shapes in either the time or frequency domain. A few of the discriminants which have resulted from GE's models are presented in the section on specific techniques. They have considered many other discriminants which have not been included as they were less successful than the ones discussed.

Most techniques which depend on a model have a fairly simple discriminant. However, getting this discriminant out of the remainder of the signal may be difficult. This is the case with bearing ball pass and race frequencies. Models do a fine job of predicting these frequencies and their harmonics, but they generally do not predict the noise levels that may overwhelm the amplitudes of the predicted frequency components. This is likely to be the case in helicopters. Also, models have not been developed to the extent that they include any significant information about the mechanical transfer function between the forcing function and the transducer locations. Typically, experimentation is necessary to obtain this information, and once obtained, it may be used in the model.

There are cases where it would appear that a combination of model evaluation and pattern recognition would be reasonable. Many pattern recognition advocates are the first to recognize this. For instance, Hamilton-Standard modified their pattern recognition scheme to favor gear mesh frequencies, shaft frequencies, and their harmonics (all frequencies derived by simple mechanical modeling). Techniques such as the Optimum Seeking Classifier of Scope Electronics require selection of specific features in order to be usable. Scope used mechanical features which were determined from models in their analysis.

In summary, it is felt that the vast volume of data necessary for pattern recognition techniques would make them very expensive to develop. However, it is conceded that the more sophisticated of these techniques are likely to be accurate predictors of helicopter condition if they are properly trained. On the other hand, techniques based on the mathematical models require far less testing, much of which can be done on test stand, and are thus easier to implement. The primary difficulty with the modeling approach is the ability to come up with a model which simulates the actual situation accurately.

GEAR VS. BEARING

For most of the diagnostic systems which have been presented, there is one type of technique used for gears and a second group of techniques used for bearings. This is reasonable since these two machine elements are distinctly different in their modes of operation. Only in pattern recognition schemes have bearings and gears been lumped together, and even then, the discriminants are likely to be different for the detection of gear failures than for bearing failures.

Most diagnostic techniques for discrete bearing faults rely on the fact that impacts will occur at a repetition rate which can be easily computed from bearing geometry. The secondary effects created by these impacts can be measured in many ways. The impact excites structural resonances and causes a transient response at the resonant frequencies of the structure. This transient can result in large peaks in the time plot. These large peaks have been used as the basis of statistical techniques such as Impact Index and composite exceedance. Other schemes use a measure of the resonant response in the frequency domain as their basis.

In general, the techniques which depend on time domain data are very dependent upon the overall signal-to-noise ratio, where signal here is interpreted as the resonant ringing excited by the fault impact. As the noise (which may include gear frequencies) becomes large, the variations caused by the ring become very small. In the case of helicopter data recorded to 5 kHz, the predominant spectral frequencies were all related to the gear mesh frequency. Since data was not taken above 5 kHz, it is not known whether the resonant peaks occur at higher frequencies.

Very little work has been done on the modeling of nondiscrete bearing faults such as mounting misalignment, manufacturing errors, etc. Again, General Electric has probably done the most analysis, with much of the work being done in their Space Division. It should be pointed out that the bearings of interest to the Space Division come from small instrument-type mechanisms and not from a high-power transmission as is the case in helicopters.

While most bearing techniques use impacts as their basis, most gear techniques use some form of harmonic and/or modulation phenomenon related to the gear mesh frequency. The modeling which has been done for gearing has not been as extensive as for bearings. A detailed physical model of gear sidebanding effects is not yet available. The appearance of gear harmonics due to normal wear has been modeled in some detail.

One difficulty which can be expected in planetary gear trains as found in helicopter transmissions is that the orientation of discrete gear faults in the planet and gear changes as the gear rotates. The fault is sometimes meshing near the transducer, while at other times the fault is meshing in a position remote from the transducer. General Electric experienced this difficulty in attempting to apply time averaging to a discrete gear fault in a CH-47 sun gear.

There is also a possibility that the gear mesh frequency is affected by bearing condition; i.e., bad bearings tend to change the gear mesh frequency and its sidebands. This has been observed by Hamilton-Standard in their test-bed data and was also pointed out as being significant in the work done by Scope Electronics in analyzing the same data.

TYPES OF SIGNAL ANALYSIS

The mode of signal analysis which is employed with the vibration data is typically a governing factor in the type of discriminant which is selected. Analysis in the frequency domain has been most prevalent in the diagnostics field. This is primarily due to the fact that in rotating machinery most mechanical phenomena can be related to some periodic occurrence which generates a specific frequency component. Helicopter data includes many discrete components which can easily be observed in a frequency analysis. Most of the identifiable peaks in the frequency spectra of helicopters are related to gear mesh frequencies, sidebands, and multiples of shaft frequency. The helicopter data analyzed in this program did not indicate any discrete bearing frequency components because of signal-to-noise levels and, perhaps, because the implanted faults in the data made available to OSU were relatively small.

It is possible, via time averaging, to enhance periodic components prior to performing frequency analysis. This increases signal-to-noise ratios and allows frequencies otherwise imbedded in noise to become distinguishable in the frequency domain. Difficulties with time summation arise from the fact that very accurate speed reference signals are required to synchronize the process. Even then, slippage in bearings may be sufficient to unsynchronize the data and thus make the averaged data somewhat meaningless. To reduce the effects of slight errors in synchronization, the time signal is often rectified prior to time averaging. This improves signal processing accuracies, but it greatly reduces the signal-to-noise enhancement capabilities of the process, since the positive and negative noise components do not totally cancel after the rectification process.

The most popular time domain data analysis technique is derived from correlation analysis. By the use of autocorrelation, signals with distinct periodicities can be detected in a highly noisy environment. However, if other periodic signals are contained in the data, the detection of the desired signal would be possible without additional preprocessing prior to performing the correlation analysis. As with time averaging, the ability to achieve accurate synchronization is crucial to the success of correlation analysis. Other time domain techniques such as covariance and various forms of cepstrum are advantageous under certain circumstances, but they still have the inherent difficulties associated with the correlation function.

Most other forms of analysis utilize some form of time waveform shape or statistical analysis. Included are Impact Index (crest factor), Limit Exceedance, and probability density analysis. Also included in waveform analysis are time averaged data and signals which are modulated. The

latter two examples require visual inspection for application of a diagnostic decision-making process. Most of the other techniques utilize the fact that the wave form contains transients resulting from discrete faults. The primary requirement of these techniques is that the transient amplitude must be significantly larger than the remainder of the signal. If this is not the case, the techniques encounter difficulty and require preprocessing in order to function properly. This would appear to be the case for use on helicopters.

In summary, frequency analysis techniques appear to contain the most diagnostic information, but in specific applications where signal and noise levels are satisfactory, other types of data analysis may prove to be superior.

RECOMMENDATIONS

Based on the results of this study, the conclusion may be drawn that there is no single technique which is at such a stage of development that immediate implementation on helicopters is advisable. There are a few techniques, primarily of the pattern recognition type, which could prove successful if enough implant data is made available. However, the cost of providing an adequate amount of data would be prohibitive. There are a number of mechanically related techniques, but these are not yet in such a state of development that widespread use is recommended at this time.

With this general conclusion in mind, recommendations in three categories have been prepared. The first category offers recommendations relative to the general direction of future research activities. Secondly, recommendations are made with respect to specific techniques which are now available. Some of these techniques show promise which further development might uncover. Finally, areas which have previously been mentioned but not explored in any detail are discussed. There are a number of phenomena which have been observed or discussed and which show promise as diagnostic tools. However, not much examination of them has been performed and little definitive information is available.

GENERAL RECOMMENDATIONS

A list of general directions for future efforts to follow (not necessarily in order of importance) would include:

1. Continued study of the modeling of physical phenomena induced by failures in gears and bearings.

2. Development of a data file containing helicopter vibration data.

3. Determination of the failure modes most prevalent in helicopter transmissions and the requirements of a diagnostic system with respect to each mode.

4. Study of the structural dynamic characteristics of the helicopter power train.

5. Study of the effects of variations in operating conditions of the helicopter on vibrations produced.

These will be discussed more completely below.

MODELING

The diagnostic systems which show the most promise have as their basis some analysis of the physical phenomena underlying the operation of the

component being monitored. For example, before narrow-band analysis of a bearing is attempted, a kinematic study must be performed to determine the characteristic rotational and pass frequencies. By performing an analysis of the physical phenomena, a much better understanding of the causes of vibration characteristics as well as the possibility of extrapolation of results is possible. Even the pattern recognition techniques which are most successful use some physical reasoning in their analysis.

For these reasons, it is recommended that further efforts in modeling the reactions produced in gears and bearings by various failure modes be performed. The primary emphasis should apply to gearing since a good deal of analysis and modeling has been performed on bearings, as evidenced by the number of diagnostic techniques using such analysis. However, little has been done successfully with gearing in this area.

It should be emphasized that while the initial studies on modeling may be performed in an artificial, test-stand environment, final evaluation should be made on actual helicopters, where the effect of interplay between other components can be determined.

DEVELOP DATA FILE

The amount of actual helicopter vibration data readily available is quite limited both in sheer volume and in frequency range. It is often quite difficult to make a decision as to the effectiveness of application of a given technique on a helicopter without actual helicopter testing. Since flying each of a number of systems would be quite unfeasible, the next best step would be to develop a file of tape-recorded data which would be sufficient for such testing. It is recommended that such a file be produced. One obvious scheme would be to have a central file for all helicopter vibration data. A standard logging format could be established, and all data taken would be made compatible with this format. Data should be acquired with a frequency range of at least 50 kHz and, hopefully, even higher ranges. A good deal more failure implant data is also needed, especially for gearing failures.

FAILURE MODE ANALYSIS

A determination should be made of the order of importance of various failure modes, both in gears and in bearings. Data is available on the type of failures which do occur, but little is available to describe the frequency of occurrence or severity of given modes. Since the sensitivity of given diagnostic techniques varies from one mode of failure to another, such information would be most useful in both designing and evaluating diagnostic systems.

STRUCTURAL DYNAMICS

Any vibration signal which has its origin in a machine or transmission will

surely be affected by mounting or structural characteristics before it reaches a transducer. For this reason, a determination of these effects must be made. Such a determination is useful in the design of diagnostic system discriminants as well as in the determination of number and type of transducers, transducer placement and mounting, and preconditioning of the signal which is required.

A study to determine the system structural characteristics would probably be composed of two parts. One would be an analytic determination of these characteristics probably via finite element or some other lumped element analysis. Either shaker or pulse excitation tests would be required to accurately determine the validity of the computer model. Once the model is available, analysis could proceed to optimize transducer placement and to determine signal transmission path transfer functions.

EFFECT OF OPERATING CONDITIONS

It has been found in the test bed program and other experimental programs that the operating conditions of a helicopter have a profound effect on the monitored vibration. However, no quantitative explanation has been found. If such an explanation were available, it could prove to be quite useful in the evaluation and development of diagnostic systems.

DEVELOPMENT OF SPECIFIC TECHNIQUES

Based on the information available, there appear to be three types of presently available techniques which merit further development. These are:

1. Further study and development of techniques which utilize resonant phenomena.

2. Study of pre-processing techniques with respect to helicopter data.

3. Study the use of pattern recognition techniques to rank discriminants and to optimize diagnostic systems.

RESONANT TECHNIQUES

There have been a number of techniques presented or discussed which utilize some type of resonant phenomenon. These phenomena include bearing race and ball resonances, transducer resonances, and structural resonances of housing and support structures. Such techniques appear to have strong possibilities for future development. They generally appear to be sensitive to failure and are relatively insensitive to unwanted signals. Because of these characteristics, they warrant further study.

PRE-PROCESSING

A number of bearing diagnostic systems run into difficulty with helicopter vibration data due to the predominance of gear mesh frequencies, harmonics, and sidebands in the signals. It might be possible, given the correct pre-processing, that such techniques might be more useful.

There are a number of processing techniques which could be utilized. For example, time averaging is a prime candidate for extracting bearing vibration from a composite signal. Autocorrelation is another technique which might be useful. Comb filtering might have the same effect. And pre-whitening may be used to eliminate the difficulty encountered with strong gear mesh components in helicopter data.

Some analysis and study should be performed to determine the feasibility or advisability of using these pre-processing techniques.

USE OF PATTERN CLASSIFIERS

The use of pattern recognition techniques as the sole basis of a diagnostic system appears to be prohibitively costly and possibly unworkable. However, if used in conjunction with other diagnostic procedures, they could prove to be quite useful. Of particular interest is the ability of these powerful statistical tools to rank the amount of information available in a group of discriminants.

As an exmaple, we might consider a ranking of information by frequency and the probability of classification using the discriminant. If a system is proposed, a ranking of this type might determine the optimum design for the evaluation system. A second use of the pattern classifiers might be to provide a quantitative rating, based on discrimination ability, for a number of candidate diagnostic systems.

NEW AREAS

There are some discriminants or analysis procedures which have been mentioned in previous investigations but not studied to any large extent. Three which show some promise are:

1. Effect of bearing failure on gear mesh sidebands.
2. Use of run-up and run-down tests.
3. Use of energy content of sidebands and harmonics.

EFFECTS OF BEARINGS ON GEARS

It has been found that the failure in a bearing increases the energy content of the gear sidebands. No quantitative or even good qualitative

explanation of this phenomenon is available. If an explanation were found, this phenomenon could possibly prove to be an acceptable failure discriminant.

RUN-UP AND RUN-DOWN TESTS

Run-up and run-down tests, i.e., tracking given frequencies while changing operating speed, are a common means of determining system resonances. It may also be possible to track on a given resonance and follow its response through a run-up test and gain valuable information on system condition.

SIDEBAND AND HARMONIC ENERGY

As failures occur in gears and bearings, greater and greater differences from pure sinusoidal operation occur, giving rise to higher sideband and harmonic energy content.

SUMMARY

A number of studies which would be useful in the development of diagnostic systems have been recommended in this chapter. The development of these recommendations into a research program is the province of the Army. It should be noted that, in the authors' opinion, a good workable vibration diagnostic system for Army helicopter usage is several years away.

Of prime importance among the recommendations are the modeling, the development of a data file, and the determination of the failure modes of interest. Other work can proceed from these. The data file will be of special use in later work.

LITERATURE CITED

1. ______________, CONCEPT FORMULATION STUDY FOR AUTOMATIC INSPECTION, DIAGNOSTIC, AND PROGNOSIS SYSTEMS (AIDAPS), FINAL REPORT - VOLUME II, Northrop Corporation, Electronics Division; USAAVSCOM Technical Report 72-20, U. S. Army Aviation Systems Command, St. Louis, Missouri, September 1972.

2. Provenzano, James, Games, John, Wyrostek, A., Ostheimer, A., and Young, J., UH-1H AIDAPS TEST BED PROGRAM FINAL TECHNICAL REPORT, Hamilton-Standard Division of United Aircraft Corp.; USAAVSCOM Technical Report 72-18, U. S. Army Aviation Systems Command, St. Louis, Missouri, August 1972.

3. Butcher, Robert R., Kirby, Russel Jr., Nakakihara, John, Watkins, T. C., UH-1 TEST BED PROGRAM FINAL REPORT, Northrop Corp., Electronics Division; USAAVSCOM Technical Report 72-19, U. S. Army Aviation Systems Command, St. Louis, Missouri, September 1972.

4. Spotts, M. F., DESIGN OF MACHINE ELEMENTS, Third Edition, Englewoods Cliffs, New Jersey, Prentice-Hall Incorporated, 1961, pp. 330-332.

5. Bisson, Edmond E., and Anderson, William J., ADVANCED BEARING TECHNOLOGY, NASA SP-38, Lewis Research Center, Cleveland, Ohio, 1965.

6. Bowen, C. W., Dyson, L. L., and Walker, R. D., MODE OF FAILURE INVESTIGATIONS OF HELICOPTER TRANSMISSIONS, Bell Helicopter Company, USAAVLABS Technical Report 70-66, Eustis Directorate, U. S. Army Air Mobility Research and Development Laboratory, Fort Eustis, Va., January 1971, AD 881 610.

7. Balderston, Harvey L., DETECTION OF INCIPIENT FAILURE IN BEARINGS, Materials Evaluation, June 1969, p. 123.

8. Love, A. E. H., A TREATISE ON THE MATHEMATICAL THEORY OF ELASTICITY, Fourth Edition, Cambridge, Mass., The University Press, 1934, p. 286.

9. Stokey, W. F., VIBRATION OF SYSTEMS HAVING DISTRIBUTED MASS AND ELASTICITY: SHOCK AND VIBRATION HANDBOOK, VOLUME I, SECTION 7, New York, McGraw-Hill, 1961, p. 36.

10. Shipley, Eugene R., GEAR FAILURES, MACHINE DESIGN, December 7, 1967.

11. Op. cit., Reference 2.

12. Klosterman, Albert L., A COMBINED EXPERIMENTAL AND ANALYTICAL PROCEDURE FOR IMPROVING AUTOMOTIVE SYSTEM DYNAMICS, Structural Dynamics Research Corporation, SAE Paper No. 720093.

13. Op. cit., Reference 9.

14. Morse, I. E., Shapton, W. R., Brown, D. L., and Kuljanic, E.,

APPLICATION OF PULSE TESTING FOR DETERMINING DYNAMIC CHARACTERISTICS OF MACHINE TOOLS, Technical paper presented at the Thirteenth International Machine Tool Design and Research Conference, University of Birmingham, Birmingham, England, September 22, 1972.

15. Wang, S. M., and Morse, I. E., TORSIONAL RESPONSE OF A GEAR TRAIN SYSTEM, ASME Paper 71-VIBR-77, Presented at Vibrations Conference, Toronto, Canada, September 8-10, 1971.

16. Laskin, I, Orcutt, F. K., and Shipley, E. E., ANALYSIS OF NOISE GENERATED BY UH-1 HELICOPTER TRANSMISSION, Mechanical Technology Incorporated; USAAVLABS Technical Report 68-41, U. S. Army Aviation Materiel Laboratories, Fort Eustis, Virginia, June 1968, AD 675457.

17. Badgley, R. H., and Laskin, I., PROGRAM FOR HELICOPTER GEARBOX NOISE DETECTION AND REDUCTION, Mechanical Technology Incorporated; USAAVLABS Technical Report 70-12, U. S. Army Aviation Materiel Laboratories, Fort Eustis, Virginia, March 1970, AD 869822.

18. Badgley, R. H., and Chiang, T., INVESTIGATION OF GEARBOX DESIGN MODIFICATIONS FOR REDUCING HELICOPTER GEARBOX NOISE, Mechanical Technology Incorporated; USAAMRDL Technical Report 72-6, Eustis Directorate, U. S. Army Air Mobility Research and Development Laboratory, Fort Eustis, Virginia, March 1972, AD 742735.

19. Bendat, Julius and Preisol, A. G., MEASUREMENT AND ANALYSIS OF RANDOM DATA, New York, J. Wiley and Sons, Inc., 1966.

20. Jenkins G., and Watts, D., SPECTRAL ANALYSIS AND ITS APPLICATIONS, San Francisco, Holden Day Incorporated, 1968.

21. Enochson, Loren D., and Otness, Robert K., PROGRAMMING AND ANALYSIS FOR DIGITAL TIME SERIES DATA, Measurement Analysis Corporation; Shock and Vibration Monograph SVM-3, Naval Research Labcratory, Washington, D. C., pp. 81-86.

22. Op. cit., Reference 9, p. 36.

23. Weichbordt, Bjorn, MECHANICAL SIGNATURE ANALYSIS: A NEW TOOL FOR PRODUCT ASSURANCE AND EARLY FAULT DETECTION, Annals of Reliability and Maintainability, Vol. 5, 1966.

24. Langenthal, Ira M., CORRELATION AND PROBABILITY ANALYSIS, SAICOR Signal Analysis Industries, Hauppage, N. Y., 1970.

25. Burrows, Laurie R. Jr., SOME ANALOG METHODS OF POWER SPECTRAL DENSITY ANALYSIS, Spectral Dynamic Corporation Technical Publication PS-1, 1968, pp. 7-8.

26. Op. cit., Reference 19, pp. 258-270.

27. REAL TIME SIGNAL PROCESSING IN THE FREQUENCY DOMAIN, Federal Scientific Corporation, Monograph #3, 1971, pp. 10-11.

28. Davis, Don, COHERENCE FUNCTION COMPUTATION, TIME/DATA, Application Note Series/No. 1, 1972, pp. 1-2.

29. Brown, D. L., and Halvorsen, W. G., APPLICATION OF THE COHERENCE FUNCTION TO ACOUSTIC NOISE MEASUREMENTS, Inter-Noise 72 Proceedings, Washington, D. C., October 4-6, 1972, pp. 417-422.

30. Kemeraltd and Childers, SIGNAL DETECTION AND EXTRACTION BY CEPSTRUM TECHNIQUES, IEEE Transactions on Information Theory, Vol. IT-18 W06, pp. 745-759, Nov. 1972.

31. Braun, S., A PRACTICAL APPROACH TO DIGITAL SPECTRA ANALYSIS VIA THE FAST FOURIER TRANSFORM, Report No. 71-C-227, General Electric Technical Information Series, August 1971, pp. 10-15.

32. Op. cit., Reference 27, p. 8.

33. Op. cit., Reference 21.

34. Harmuth, Henning F., TRANSMISSION OF INFORMATION BY ORTHOGONAL FUNCTIONS, Second Edition, New York, Springer-Verlag, 1969, p. 7.

35. Braun, S., EXTRACTION OF PERIODIC SIGNALS BY COMB FILTERS: A GENERALIZED APPROACH, Report No. 71-C-209, General Electric Technical Information Series, July 1971, pp. 16-18.

36. Broch, Jens Trampe, MECHANICAL VIBRATION AND SHOCK MEASUREMENTS, Naerum, Denmark, Bruel and Kjaer, 1972, p. 122.

37. Misialek, R., Personal Communication, NAVSEC, Philadelphia shipyard.

38. Op. cit., Reference 1.

39. Nagy, George, STATE OF THE ART IN PATTERN RECOGNITION, Proceedings of IEEE, Vol. 56, No. 5, May 1968, pp. 836-862.

40. Tou, Julius T., Ed., ADVANCES IN INFORMATION SYSTEMS SCIENCE, Vol. I, New York, Plenum Press, 1969, pp. 173-244.

41. Mendel, J. M., and Fu, K. S., Ed., ADAPTIVE, LEARNING, AND PATTERN RECOGNITION SYSTEMS, New York, Academic Press, 1970, pp. 3-161.

42. Nilsson, N. J., LEARNING MACHINES: FOUNDATIONS OF TRAINABLE PATTERN CLASSIFYING SYSTEMS, New York, McGraw-Hill, 1965.

43. SONIC ANALYZER DIAGNOSTIC SYSTEM, Curtiss-Wright Corporation, SP-457, September 1970.

44. THE CURTISS-WRIGHT DIAGNOSTIC SONICS ANALYSIS TECHNIQUE, Curtiss-Wright Corporation, SP 15-23, December 1964.

45. Frarey, J. L., Handjani, H., SONIC ANALYSIS FOR TURBINE ENGINES, PD-552, Presented at the 12th Annual ISA Aerospace Instrumentation Symposium, May 4, 1966.

46. Hogg, G. William, EVALUATION OF THE EFFECTIVENESS OF USING SONIC DATA TO DIAGNOSE THE MECHANICAL CONDITION OF ARMY HELICOPTER POWER TRAIN COMPONENTS, USAAMRDL Technical Report 72-30, Eustis Directorate, U. S. Army Air Mobility Research and Development Laboratory, Fort Eustis, Virginia, May 1972, AD 745089.

47. Op. cit., Reference 46.

48. Demuth, Hal P., Rudd, Dr. T. James, HELICOPTER GEARBOX SIGNATURE ANALYSIS, Ensco Incorporated; Proposed Program, August 16, 1972.

49. ____________, COMPOSITE EXCEEDANCE TECHNIQUE FOR STATUS MONITORING OF MECHANICAL COMPONENTS, Notes from the Airesearch Manufacturing Company, The Garrett Corporation.

50. Kukel, J., Ziebarth, H. K., Chang, J. D., Minnear, J. E., Lau, J. L., TURBINE ENGINE DIAGNOSTIC CHECKOUT SYSTEM, Airesearch Manufacturing Company, The Garrett Corporation, Technical Report AFAPL-TR-71-33, Air Force Aero Propulsion Laboratory, Wright-Patterson Air Force Base, Ohio, June 1971.

51. Roos, C. H., VIBRATION SIGNATURE ANALYSIS OF BEARINGS AND ELECTRONIC PACKAGES, SI-460, Presented at 41st Shock and Vibration Symposium, Colorado Springs, Colo., Oct. 27-29, 1970.

52. Kirschmann, A. E., TF-34 ENGINE VIBRATION ANALYZER, FINAL REPORT, General Electric Company, Contract 62269-70-C-0315, Work Item 7, NASC, Washington, D. C., 10 June 1971.

53. Weichbordt, Bjorn, Bowden, Frank J., INSTRUMENTATION FOR PREDICTING BEARING DAMAGE, General Electric Company, Technical Report RADC-TR-69-437, Rome Air Development Center, Griffiss Air Force Base, New York, March 1970, AD 869633.

54. Weichbrodt, B. and Smith, K. A., SIGNATURE ANALYSIS--NONINTRUSIVE TECHNIQUES FOR INCIPENT FAILURE IDENTIFICATION. APPLICATION TO BEARINGS AND GEARS, Report No. 70-C-364, General Electric Technical Information Series, October 1970.

55. Last, L., FOBW ANALYSIS OF SONIC AND VIBRATION SIGNALS, Notes.

56. Soelecito, William E., BINARY WORD ANALYSIS, Presented at Signature Analysis and Diagnostics Conference, General Electric Company, June 11-12, 1968.

57. Last, L., HELICOPTER TRANSMISSION SONIC/VIBRATION ANALYZER PROGRAM (NOTES), General Electric Company, February 1970.

58. Op. cit., Reference 52.

59. Frarey, J. L., DEVELOPMENT OF GEAR FAILURE DETECTION METHODS, Mechanical Technology, Inc., Report No. MTI70TR76, Office of Naval Research, Washington, D. C., December 31. 1970, AD-720 735.

60. Haskin, L. B., Schlereth, F. H., MECHANICAL FAILURE DETECTION General Electric Company, Office of Naval Research, Washington, D. C.

61. Thompson, R. A., Weichbrodt, Bjorn, GEAR DIAGNOSTICS AND WEAR DETECTION, ASME Paper No. 69-VIBR-10, Presented at Vibration Conference, Philadelphia, Pa., March 30-April 2, 1969, pp. 1-4.

62. Babkin, S. A., and Anderson, J. J., MECHANICAL SIGNATURE ANALYSIS OF BALL BEARINGS BY REAL TIME SPECTRUM ANALYSIS, Publications of Federal Scientific Corp.

63. Catlin, J. B., IMPROVED MAINTENANCE OF MACHINERY THROUGH "BASE LINE" VIBRATION MEASUREMENTS, ASME Paper No. 72-PEM-1, Presented at the Plant Engineering and Maintenance Conference, Baton Range, La., October 15-18, 1972.

64. Op. cit., Reference 2.

65. PROGRAM BRIEF: A NEW DETECTION CONCEPT FOR ROLLING ELEMENT BEARING QUALITY CONTROL TESTING, Mechanical Technology, Inc., MTI Report MSPB-24.

66. Broderick, J. J., Burchill, R. F., Clark, H. L., DESIGN AND FABRICATION OF PROTOTYPE SYSTEM FOR EARLY WARNING OF IMPENDING BEARING FAILURES, Mechanical Technology, Inc., Control Number MFS-21877, George Marshall Space Flight Center, NASA, Huntsville, Alabama, January 1972.

67. Kellum, Gary B., SIGNATURE ANALYSIS OF PLANT EQUIPMENT, ASME Paper 71-PET-14.

68. Minnear, J. E., Ziebarth, H. K., Law, J. L., Chang, J. D., Reynolds, W., and Kukel J., ADVANCED DIAGNOSTIC SENSOR APPLICATIONS TECHNOLOGY, Airesearch Manufacturing Company, The Garrett Corporation; Technical Report AFAPL-TR-72-59, U. S. Air Force Systems Command Air Force Propulsion Laboratory, Wright-Patterson Air Force Base, Ohio, June 1972, p.119.

69. Op. cit., Reference 7.

70. Op. cit., Reference 3.

71. Scott, Julian, and Herskowitz, Alan, Personal Communications, Scope Electronics.

72. SHOCK PULSE METER, SKF MEPA-10A, Shock Pulse Instrumentatation Discussion by SKF.

73. Kolsky, H., STRESS WAVES IN SOLIDS, Oxford, The Clarendon Press, 1953.

74. Johnson, W., IMPACT STRENGTH OF MATERIALS, London, England, Edward Arnold Limited, 1972.

75. Bessman, J. W. and J. W. Glenn, "Optimum-Seeking Pattern Classifier," SCOPE Electronics Inc. Technical Memorandum, No. TM-159, April 1969.

76. Bessman, J. W., "Feature Selection in the Design of Pattern Recognizers," SCOPE Electronics Inc. Technical Memorandum, No. TM-221, May 1972.

77. Andrews, H. C., INTRODUCTION TO MATHEMATICAL TECHNIQUES IN PATTERN RECOGNITION, John Wiley and Sons, Inc., New York, 1972.

71. Scott, Julian, and Herskowitz, Alan, Personal Communications, Scope Electronics.

72. SHOCK PULSE METER, SKF MEPA-10A, Shock Pulse Instrumentatation Discussion by SKF.

73. Kolsky, H., STRESS WAVES IN SOLIDS, Oxford, The Clarendon Press, 1953.

74. Johnson, W., IMPACT STRENGTH OF MATERIALS, London, England, Edward Arnold Limited, 1972.

75. Bessman, J. W. and J. W. Glenn, "Optimum-Seeking Pattern Classifier," SCOPE Electronics Inc. Technical Memorandum, No. TM-159, April 1969.

76. Bessman, J. W., "Feature Selection in the Design of Pattern Recognizers," SCOPE Electronics Inc. Technical Memorandum, No. TM-221, May 1972.

77. Andrews, H. C., INTRODUCTION TO MATHEMATICAL TECHNIQUES IN PATTERN RECOGNITION, John Wiley and Sons, Inc., New York, 1972.

SELECTED BIBLIOGRAPHY

______________, CSS-3, BEARING FAILURE PREDICTION SYSTEMS, Technical Note, Computer Signal Processors, Inc.

Baird, B. C., INCIPIENT FAILURE DETECTION IN ANTIFRICTION BEARINGS, Presented at the 27th Annual Petroleum Mechanical Engineering and Pressure Vessels and Piping Conference, New Orleans, Louisiana, 17-21 September 1972.

Bannister, R. L., and Donata, V., SIGNATURE ANALYSIS OF TURBOMACHINERY, Sound and Vibration, September 1971.

Borhaug, J. E., and Mitchell, J. S., APPLICATIONS OF SPECTRUM ANALYSIS TO ON-STREAM CONDITION MONITORING AND MALFUNCTION DIAGNOSIS OF PROCESS MACHINERY, Technical Note, Dow Industrial Services, Turbomachinery Engineering Service.

Chalfin, A., Staton, G. R., AUTOMATIC INSPECTION AND DIAGNOSTIC SYSTEM FOR ARMY TACTICAL VEHICLES, IEEE Transactions on Aerospace and Electronics Systems, Vol. AES-2, No. 3, May 1966.

Cochran, W. T., Cooley, J. W., Favin, D. L., Helms, H. D., Kaenel, R. A., Lang, W. W., Maling, G. C., Nelson, D. E., Rader, C. M., Welch, P. D., WHAT IS THE FAST FOURIER TRANSFORM?, IEEE Transactions on Audio and Electroacoustics, Vol. AU-15, No. 2, June 1967.

Cortina, E., Engel, H. L., Scott, W. K., PATTERN RECOGNITION TECHNIQUES APPLIED TO DIAGNOSTICS, SAE Paper 700497, Presented at Mid-Year Meeting, Detroit, Mich., May 18-22, 1970.

Dickinson, C. B., VIDEC-VIBRATION ANALYSIS AND DEVIATION CONCEPT, Presented to the Gulf Section, The Society of Naval Architect and Marine Engineers, September 24, 1971.

DiRita, R. A., George, D. L., ACOUSTIC MAINTENANCE AIDS, UNIVAC Report No. 94-733-1, March 1969.

Downham, E., Woods, R., THE RATIONALE OF MONITORING VIBRATION ON ROTATING MACHINERY IN CONTINUOUSLY OPERATING PROCESS PLANT, A.S.M.E. Paper No. 71-VIBR-96, Presented at the Vibrations Conference, A.S.M.E., Toronto, Canada, September 8-10, 1971.

Gaberson, H. A. and Pal, D., DIGITAL FOURIER ANALYSIS OF MECHANICAL SHOCK DATA, Report of Naval Civil Engineering Laboratory, Port Hueneme, California.

George, D. L., ACOUSTICS AND VIBRATION IN QUALITY CONTROL, DESIGN, AND MAINTENANCE, Proceedings of the UNIVAC Data Processing Division, Second Engineering Symposium, May 1967.

Lundgaard, B., THE RELATIONSHIP BETWEEN MACHINERY VIBRATION LEVELS AND

FAILURES, Prepared for Presentation to Pacific Northwest Section of the Society of Naval Architects and Marine Engineers, November 19, 1971.

Markevitch, B. V., Rodal, D. R., and Brown, H., THE USE OF OPTICAL PROCESSING OF ENGINE VIBRATION DATA AS A MEANS OF PREDICTING FAILURES, Presented at the Seventh Annual FAA International Aviation Maintenance Symposium, Oklahoma City, December 7-9, 1971.

Pavlidis, T, and Geng Seng Fang, APPLICATION OF PATTERN RECOGNITION TO FAULT DIAGNOSIS OF INTERNAL COMBUSTION ENGINES, Princeton University, U. S. Army Research Office, Durham, North Carolina, September 1971, AD-747 334.

Schlereth, F. H., DETECTION OF INCIPIENT MACHINE FAILURE THROUGH VIBRATION ANALYSIS, A.S.M.E. Paper No. 72-DE-55, Presented at the Design Engineering Conference & Show, Chicago, Illinois, May 8-11, 1972.

Sturgeon, L. F., ACOUSTIC SIGNATURE ANALYSIS, General Electric Internal Memorandum, Prepared by the Space Division, November 15, 1972.

Sturgeon, L. F., ACOUSTIC CHARACTERIZATION OF PRECISION BALL BEARINGS, Presented at International Ball Bearing Symposium, Cambridge, Massachusetts, June 5-7, 1973.

White, C. J., DETECTION OF FAULTS IN COMPLEX GEARBOXES BY ANALYSIS OF VIBRATION, Westland Helicopters Limited Report No, RP. 372.

Wotipka, J. L. and Zelenski, R. E., IDENTIFICATION OF FAILING MECHANISMS THROUGH VIBRATION ANALYSIS, A.S.M.E. Paper No. 71-VIBR-90, June 1971.

APPENDIX I
COMPANIES AND INDIVIDUALS CONTACTED

In the course of this study, aid and information were obtained from a large number of individuals and companies. This appendix lists these companies and individuals and the type of information obtained.

The first column lists the name of the company and the city in which it is located. The second column lists the individuals contacted. The third, fourth, and fifth columns list the type of contact--whether by phone (Ph), letter (Lt), or visit. In the case of a personal visit, the date is included. The final column lists the response; i.e., the type of work being done, the facilities available, general comments on diagnostic techniques, etc.

In an effort to contact many of the people working in the diagnostics field, the investigators attended the Mechanical Failure Preventions Group (MFPG) meeting at the National Bureau of Standards, in Gaithersburg, Md. on Nov. 8-10, 1972. A note is made in the response column of people contacted at this meeting.

There are possible inaccuracies in the information contained in this appendix since the information was gathered over the course of a year, and there may have been changes in both the status of the individual and the work done by a particular company which has not at this time become available to the investigators.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Agbabian Associates Los Angeles, California	Lloyd Carlson Loren Enochson		X	8/8/72	Data analysis procedures employed by them and the capabilities of Macran Digital Processing Package sold by them were discussed. They suggested use of the coherence function to compare good and bad data.
Air Force Aero-Propulsion Laboratory Wright-Patterson Air Force Base, Ohio	K. Hamilton	X		8/3/72	The lab has sponsored the TEDS (Turbine Engine Diagnostics System) program with Garrett Corporation. Further work is being performed on a C-5A by General Electric Company.
Algernon Blair, Inc. Montgomery, Alabama	President		X		Company not involved in any work of interest to the study.
Allison Laboratories Austin, Texas	E. V. Parsons		X		None.
Ampex Corp. Redwood, California	Dr. Wm. A. Gross Robert V. Markevitch	X	X		Discussed optical processing of frequency spectra. Tried to find information on a literature search they conducted a few years previously but was not available. Several reports on their techniques have been published.
Avco Lycoming Stratford, Connecticut	Rudy Hohenberg		X		Information sent concerning the T55-L-11 analysis system.
Avco Precision Products Richmond, Indiana	Director of Engineering		X		None.
Army CDC Maintenance Agency Aberdeen, Maryland	A. H. Layman		X		None.
Army Tank-Automotive Command Warren, Michigan	Don Rees		X		None.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Army Aviation Systems Command (AMSAV-ERS) St. Louis, Missouri	Lamoine Plog Robert Martin	X	X	2/21/72	Discussed conduct of AIDAPS Test Bed Program. Obtained data tapes prepared by Hamilton-Standard during Test Bed Program. Discussed general philosophies concerning diagnostic systems and future plans.
Army Aviation Systems Command (ARADMAC) Corpus Christi, Texas	Hugh Bull	X			Discussed use of diagnostic devices including possible use of SKF shock pulse meter at ARADMAC.
Battelle Memorial Institute Columbus, Ohio	David B. Hamilton R. Snedicker				Discussed their work in the area of elastohydrodynamics and bearing design with possible application to diagnostic systems. Presently not performing specific diagnostic analysis.
Battelle Northwest Richland, Washington	Phillip H. Hutton		X		None. Active in acoustic emission work.
Bell and Howell Electronics and Instruments Group Pasadena, California	W. E. Rust		X		Reply with information concerning CEC transducer division work. Their primary activities are in the areas of transducer technology and data acquisition systems. Analysis technique: narrow-band analysis.
Bell Helicopter Co. Dallas, Texas	C. Bowen D. Laingor	X	X		Discussed failure analysis work with C. Bowen. They are interested in diagnostic work. Most of their work has been done with oil analysis. Talked with D. Laingor at M.F.P.G. His testing group is doing work on the AIDAPS.
Bissett-Berman Corp. Santa Monica, California	E. Cortina		X		None.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
The Boeing Company Seattle, Washington	Harvey I. Balderston J. Dubies		X		None. They performed considerable high-frequency bearing analysis in 1960's. They looked at resonances and acoustic emission. Mr. Balderston has retired, and his group has moved to Houston, Texas.
Boeing Incipient Failure Dept (IFD) Houston, Texas	Bruce C. Baird		X		Information sent concerning incipient failure detection. This department is a derivative of Balderston and has done some high-frequency data analysis. Present techniques are directed toward petrochemical industry.
Boeing Vertol Philadelphia, Pennsylvania	Ernie Hinterkeuser Al Lemanski John Mack		X	8/30/72	A discussion of their use of narrow-band and discriminant analysis of helicopter power trains was held. Vertol has taken implant data from a helicopter transmission test stand for the Navy. Mr. Mack is involved in an in-house diagnostic program at Boeing and visited OSU in June 1973 to discuss vibration diagnostics.
Bolt, Beranek, and Newman Boston, Massachusetts	W. Patterson	X			They are not doing much work specifically in diagnostics but are involved heavily in noise work and data analysis.
Computer Signal Processors, Inc. Burlington, Massachusetts			X		Received information on a narrow-band analysis system which they sell that uses FFT processing. A unique capability is a "zoom" feature to expand frequency resolution.
Curtiss-Wright Corp. Caldwell, New Jersey	C. J. Zabriskie	X	X		Discussed use of sonic analyzer as troubleshooting tool on Navy jet engines. Their only present activity is with Navy.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Detroit Diesel Allison Division of General Motors Indianapolis, Indiana	R. C. Bourke R. E. Henderson		X		Expressed interest in project and enclosed their report, "Vibration Velocity, A Measure of the Destructive Potential of Vibration," A-9628, by R. F. White. They use 1/3 octave band analysis of vibration velocity data for gas turbine diagnostics and detect unbalance, fuel pump problems, seal rubs, and diffuser/splitter problems.
Digitek Corp. Los Angeles, California	Allan Piersol		X		None.
Dow Industrial Services Walnut Creek, California	John Mitchell	X	X		Enclosed three manuscripts concerning work in turbo-machinery area relating to vibration diagnostics and narrow-band vibration studies.
Dunegan Corp. Livermore, California	Harold I. Dunegan		X		Enclosed technical reports on acoustic emission testing and described briefly the type of research done.
Dytronics Columbus, Ohio	Paul Ryan	X			Produces vibration analysis equipment. Suggested cross-correlation of signal with reference data for diagnostic purposes.
E. I. DuPont de Nemours and Co Wilmington, Delaware	J. Lynch, M. Todd, D. Mellen		X	8/31/72	DuPont Development Labs have been actively performing "in-house" diagnostic functions for several years. Their primary concern is with industrial machinery, and the primary application is narrow-band analysis.
Endevco Corp. Pasadena, California	V. L. McKelvy	X	X	8/8/72	They produce transducers which have been used by others in diagnostic systems. Discussed advance transducers design, including high-frequency and acoustic emission transducers. Also discussed a new tracking filter they are marketing which is being used for helicopter vibration monitoring by Teledyne. Transducers are being developed to measure vibration to 500 kHz and higher.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Ensco Inc. Springfield, Virginia	Charles L. Gerhardt Dr. James Rudd	X	X		Dr. Rudd visited OSU and discussed proposed helicopter diagnostic techniques utilizing stochastic correlation and spectral correlation. Talked with them at M.F.P.G.
Esso Research and Engineering Linden, New Jersey	Director of Mechanical Engineering		X		None.
Federal Scientific Corp. New York, New York	John J. Anderson Richard S. Rothschild L. A. Schwartz		X		They produce spectrum analyzers which have been used for diagnostic purposes. They do not, however, perform diagnostic work or market any diagnostic techniques. Talked to J. Anderson at M.F.P.G.
Frankford Arsenal Philadelphia, Pennsylvania	R. J. Brachman J. Hoffman		X	8/30/72	They have funded the MAIDS program, an automated diagnostic system used to determine the condition of tank engines prior to overhaul. The system does not rely heavily on vibration analysis. Involved in narrow-band analysis of machine vibration. Made a presentation at M.F.P.G.
Franklin Institute Research Lab Philadelphia, Pennsylvania	I. Leonard		X		None.
Garrett Corp. Airesearch Manufacturing Co. Torrance, California	Hans Ziebarth J. D. Chang	X	X	8/7/72	They have performed various analysis procedures including narrow-band work in conjunction with the TEDS program. Also discussed prognosis work performed for Ft. Eustis and the limit exceedance technique developed in that program. They have proposed several techniques for diagnostics and have expressed interest in high-frequency resonances and shock pulse techniques as well as pattern recognition schemes such as their "likelihood index."

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
General American Transportation Corp. Niles, Illinois	A. H. Hehn		X		None.
General Dynamics Corp. Electric Boat Division New London, Connecticut	K. A. Bowen	X	X		Narrow-band work has been done with applications to submarines. Much of this work is classified and unavailable to OSU.
General Dynamics Metrology Engineering Center Pomona, California	P. Upton		X		None.
General Electric Co. Aircraft Equipment Division Binghamton, New York	Larry Last	X	X	8/28/72	Discussed diagnostic procedures used by G.E., including time averaging, impact index, comb filtering, and gear discriminants. They are planning to market special-purpose diagnostic instrumentation. Also discussed TF-34 diagnostic analyzer and Navy helicopter gear diagnostic data taken by Boeing Vertol and analyzed by G.E. The FOBW analyzer was also discussed. Mr. Last supplied us with several G.E. reports, including analysis of data for CH-47 transmission implant tests.
General Electric Co. Electronics Lab Syracuse, New York	W. E. Sollecito		X		Referred to R&D Center. Work had previously been performed on the FOBW analyzer and G.E. MTI gear diagnostics project. Not too active in diagnostics at this time.
General Electric Co. Flight Propulsion Division Cincinnati, Ohio	A. J. Kasak		X		Referred to L. Last. G.E. is presently involved in a program to build and fly diagnostic equipment developed in the Air Force TEDS program.
General Electric Co. Gas Turbines Division Cincinnati, Ohio	Ken B. Kochanski		X		Narrow-band and crest factor analysis is used in troubleshooting gas turbines in test stands.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
General Electric Company Research and Development Schenectady, New York	Kenneth Jenkins Dr. John Wallach	X	X	8/15/72	Their work performed over the past 6-8 years was discussed. An operational crest factor meter was given to the Avionics group for development. They have done considerable "in-house" work on fault, modeling and diagnostic systems, much of which is company confidential and was unavailable to OSU.
General Radio Co. West Concord, Massachusetts	R. W. Raymond Richard K. Eskeland		X		Provided names of people using their equipment for diagnostics. They are not developing or using diagnostics techniques. One of their salesmen claims their 1/3 octave real time analyzer was being used for submarine diagnostics, but this claim was not verified.
Goddard Space Flight Center Greenbelt, Maryland	Technology Utilization Officer		X		None.
Grumman Aviation Engineering Corp. Bethpace, New York	William Brenner	X	X		They have performed diagnostic analysis on aircraft and in Grumman's now-defunct space shuttle program. No specific details were obtained.
Hamilton-Standard Division of United Aircraft	A. Wyrostek	X	X	8/17/72	The work done in the AIDAPS Test Bed Program was discussed. At the time of the visit, no other vibration diagnostic work was being performed.
I.B.M. Rochester, Minnesota	Richard Zelenski J. L. Wotipka	X	X		They have applied narrow-band analysis to the diagnosis of machine components. They have also considered pattern recognition techniques with only marginal success. Talked with Wotipka at MFPG.
Illinois Institute of Technology Research Institute Chicago, Illinois	Henry G. Tobin		X		None. IIT has performed several diagnostic studied for the Air Force with particular emphasis on transducers for gas turbines.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Industrial Technical Corp. Baton Rouge, Louisiana	G. B. Kellum		X		Narrow-band analysis has been performed on pumps, compressors, and other equipment associated with the petrochemical industry. They have been involved with high-frequency analysis.
Inficon, Inc. East Syracuse, New York	Dr. Fred H. Schlereth		X		None. Dr. Schlereth was very active in diagnostic work while at G.E.-Syracuse. No knowledge of his activities at Inficon.
Ingalls Shipbuilding (Litton) Pacagoula, Mississippi	Charles B. Dickinson		X		Enclosed copy of his paper on the vibration analysis and deviation concept. Diagnostics work utilizing narrow-band analysis. Work on ship machinery which is being done for Maritime Administration. Analysis is predominantly narrow-band.
IRD Mechanalysis Worthington, Ohio	Bob Ellis	X		10/7/72	Discussed their use of narrow-band analysis which has been performed on ship machinery. Their techniques are predominantly used for unbalance detection and gross problems in heavy machinery.
Lockheed RYS Canyon Research Lab Burbank, California	M. Gustafson		X		None. Wrote to them after Cheyenne cut back. Interest was probably at low ebb.
Lockheed-California Co. Burbank, California	James R. Eatherly		X		None. Same comment as above.
M.B. Electronics New Haven, Connecticut	R. E. Maly		X		Enclosed information on their digital control systems, but did not indicate any particular vibration diagnostics capabilities. From previous discussions MB was at one time developing a discrete frequency detector for vibration analysis; no further communication.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Mechanical Technology Inc. (MTI) Latham, New York	John Frarey Robert N. Reimherr Don Wilson R. Badgley	X	X	8/16/72	Their high-frequency bearing analyzer was discussed. D. Wilson presented some run-up data used in trouble-shooting. A discussion of noise work done on helicopters was held. Also listened to an MTI presentation at Ft. Eustis. MTI was working on bearing analyzers for NASA and an automotive company.
Melpar An American-Standard Co. Falls Church, Virginia	Joseph C. Leifer		X		None. They have done some diagnostic system development for USAAVLABS. Predominantly dealt with data acquisition hardware.
Midwest Aero Industries Corp. Royal Oak, Michigan	J. J. Sherlock		X		None.
Midwest Research Institute Kansas City, Missouri	G. E. Gross		X		Company not involved in any work of interest to this study.
NASA-Langley Research Center Hampton, Virginia	H. B. Edwards		X		None.
NASA-Lewis Research Center Cleveland, Ohio	P. T. Chiarito		X		They have developed some bearing instrumentation but are not deeply involved in vibration diagnostics.
Naval Air Systems Command Washington, D.C.	Holly Jones T. A. Lyle Poppert	X	X		Referred to work at Trenton.
Naval Air Propulsion Test Center Trenton, New Jersey	J. E. Flynn		X	8/31/72	They are using G.E. [illegible]yzer on a TF-34 engine in a test stand.
Naval Avionics Facility Indianapolis, Indiana	R. Shinkle		X		They have performed some work using spectral delays to bring signals out of noise. Predominantly narrow band.
Naval Ordnance Station Structural Analysis Dept. Louisville, Kentucky	Gerald Nicolas		X		Funding work at U. of Cincinnati to develop a vibration-related quality control inspection technique using a Hewlett-Packard Fourier analyzer.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Naval Ship Engineering Center (6762) Philadelphia, Pennsylvania	R. Misialek	X	X	9/7/72	Discussed use of narrow-band analysis on marine machinery. Discussed vibration measurement accuracy and transducer mounting. They do a lot of in-house vibration analysis and have excellent data analysis capability.
Naval Ship Engineering Center Hyattsville, Maryland	J. K. Miska		X		None.
Naval Ship Research and Development Center Annapolis, Maryland	A. R. Schrader		X		None.
Naval Undersea Research and Development Center San Diego, California	Technical Director		X		None.
Navy Submarine Base Acoustical Research and Development Division, Code 780 Groton, Connecticut	R. Y. Chapman		X		Unable to discuss related work since it was classified.
Northrop Corporation Hawthrone, California	Dr. R. Lynch J. Reis		X	8/9/72	Discussed work on AIDAPS Test Bed Program as well as other systems. Work is to be performed on running a 90° gearbox to failure for USAAMRDL. At meeting at Ft. Eustis, discussed other signal processing techniques which Northrop feels have merit. They have a digital data processing facility for analyzing vibration data. It has a minicomputer and CRT output. They are predominantly pattern recognition oriented. Talked to J. Reis at MFPG.
Pennsylvania State Univ. Ordnance Research Lab. State College, Pennsylvania	L. Pharo		X		None.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Philadelphia Gear Corp. King of Prussia, Pennsylvania	W. A. Bradley		X		Information sent concerning his paper in Chemical Engineering, May 1, 1972 and ASME 72-PEM-5 containing uses of narrow-band analysis for gear quality control.
Philco-Ford Corp. Astronutronic Division Newport Beach, California	Karl-Heinze Lohse J. R. Welch		X		None.
Production Measurements Corp. Hilliard, Ohio	A. J. Baumeister	X			Produce vibration analysis equipment. Particularly interested in analysis of large machinery.
Puget Sound Naval Shipyard Perra-CV 2212 Bremerton, Washington	W. Matheson		X		None.
Radio Corporation of America (RCA) Astro-Electronics Division Princeton, New Jersey	E. Schliesen	X			Discussed work on diagnostics. They are starting some diagnostics work.
Research Foundation of the State University of New York Albany, New York	Dr. E. Parson R. W. Fitzpatrick		X		Some work done on pure pattern recognition not related to vibration diagnostics.
Shaker Research Corp. Latham, New York	J. Frarey D. Wilson				Company started in 1973 by former MTI employees. Interested in general diagnostics work.
Scope Electronics Inc. Reston, Virginia	Al Herskowitz Julian Scott		X	9/8/72	Discussed the use of their optimum seeking classifier computer routine in the development of diagnostic system. They have also visited OSU and have performed pattern recognition analysis on helicopter data for OSU. They are very knowledgable of pattern recognition techniques and have been active in ASW and vehicle identification.
Shell Development Company Emoryville, California	Tripp F. A. Cleland		X		None.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Signal Analysis Industries Corp. Hauppauge, New York	Frank Kasper, Jr.		X		None. They manufacture a real-time frequency analyzer but have not directly performed any diagnostic studies.
Sikorsky Helicopter Stratford, Connecticut	L. Burroughs		X		Have been doing some vibration monitoring of helicopter gears.
SKF Industries Inc. King of Prussia, Pennsylvania	Paul L. Howard P. Madden	X	X	9/6/72	The MEPA shock pulse analyzer was demonstrated. It is a currently available system. This system was not [illegible] available to OSU for further analysis. The analyzer was developed and is manufactured in Sweden. SKF's stateside capabilities related to this analyzer are largely marketing oriented. SKF also performed an extensive bearing vibration study about 10 years ago. Talked with them at MFPG.
Solar Division of International Harvester San Diego, California	B. Kerr Kelly		X	8/10/72	Work has been with narrow-band analysis but primarily in the area of trouble-shooting. Mr. Kelly has analyzed some airborne helicopter data but not for diagnostics purposes.
Southwest Research Institute San Antonio, Texas	F. N. Kusenberger		X		None. SRI has been active in gear and bearing lubrication and vibration research in the petrochemical and gas compressor fields, but we are not aware of their capabilities in diagnostics area. They have also done some acoustic emission work.
Spectral Dynamics San Diego, California	A. C. Keller W. Hawkins L. Burrow	X	X	8/10/72	Discussed use of spectrum analysis equipment they produce for use in diagnostics. They furnished OSU with a real-time analyzer for use during this study.
Sperry Rand Corporation (UNIVAC) Radiation Control Group Philadelphia, Pennsylvania	R. A. DiRita		X		Enclosed reports related to vibration diagnostics. They primarily use narrow-band analysis. They plotted spectra vs. time to detect bearing failures.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Structural Dynamics Research Corp. (SDRC) Cincinnati, Ohio	G. Vollbracht J. Lemon W. Morgan	X		7/25/72	The primary emphasis of work has been in transfer function analysis and troubleshooting. Narrow-band analysis of vibration and noise signals for diagnostic purposes has been performed, predominantly in heavy machinery industries.
SUNY @ Ft. Schuyler State Maritime College Bronx, New York	A. Kramer		X		Unable to supply current work.
Teledyne Systems, Inc. El Segundo, California	A. Naipo		X		Systems for data collection have been built for use on CH-47 at Ft. Rucker. Narrow-band analysis only predominant emphasis on shaft frequencies and harmonics.
Time/Data Corp. Palo Alto, California	C. L. Heizman Steve Barber		X		Produced FFT-digital spectrum analyzers. Unit was demonstrated at OSU and some data was analyzed with it. Very powerful machine for applying different types of data analysis.
Timken Roller Bearing Co. Canton, Ohio	Gary Bowen	X			No work being done.
University of Cincinnati Cincinnati, Ohio	Dave Brown		X	7/25/72	A 3-D spectral analysis system has been built using a color TV picture tube and digital computer. The system is to be used in run-up tests of machinery and for diagnostics and quality control measurements. The system has the ability to compensate for structural dynamics and can display a Campbell diagram (Amp-Freq-Time) with amp depicted with colors.
University of Virginia School of Engineering Charlottesville, Virginia	Dr. E. J. Gunter		X		Sent list of available papers (PhD. and M.S. dissertations and theses) on subject of bearing analysis. Not related to diagnostics.

COMPANY TITLE/ADDRESS	INDIVIDUALS CONTACTED	PH	LT	VISIT	RESPONSE
Vibra-Metrics Inc. East Haven, Connecticut	John E. Judd		X		Expressed interest in project, but could be of no help at present time.
Westinghouse Electric Corp. Lester, Pennsylvania	R. L. Bannister G. B. Brandt		X		Enclosed paper "Signature analysis of turbo-machinery," and expressed interest in program. They have largely been involved with narrow-band analysis techniques.
Westland Helicopter Yeovil, England	O L. Fitzwilliams				Received reports on narrow-band analysis performed on helicopter transmissions, from J. Mack of Boeing Vertol. They monitor lower shaft harmonics to determine gear condition.

APPENDIX II

A GLOSSARY OF TERMS USED IN THE IDENTIFICATION AND PREDICTION OF MECHANICAL FAILURES

The Mechanical Failures Prevention Group (MFPG) is an informal voluntary association of interdisciplinary technical specialists from industry, educational institutions, and government. It was originally organized by the Office of Naval Research and is now sponsored by the National Bureau of Standards. It has been operated by these agencies with the cooperation of other government agencies to serve the interests of federal agencies concerned with the reduction of incidence and consequences of mechanical failures.

This glossary has been proposed by the MFPG to be used as the definition of terms frequently used in the identification and prediction of mechanical failures. The work of preparing the definitions was performed by the Diagnosis, Detection, and Prognosis Technical Committee of the MFPG.* The terms are presented in alphabetical order.

Classification - Implies that a decision rule has been identified, on the basis of which it is possible to classify waveforms.

Degradation - The act of impairing in respect to some physical property.

Detect - To sense the occurrence of a specific statistic or discriminant.

Detection Equipment - Equipment (sometimes called the detector) used to implement the decision rule.

Diagnosis - The art or act of identifying a condition from its signs and symptoms.

Diagnostic Phenomenon - A physical event or condition relatable to, or reflecting, the mechanical or structural condition of an equipment component.

Diagnostic Scoring - An indication of the accuracy of the diagnosis when waveforms are processed by a given technique.

Diagnostic Sensitivity - A measure of a technique's ability to sense changes in the mechanical condition of an equipment component at an early stage.

Diagnostic Technique - A failure detection method directed at a specific diagnostic phenomenon. A diagnostic technique consists of a sensing technique, a data processing technique, and a data analysis technique.

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*Schlereth, F. H. (Editor), GLOSSARY OF TERMS USED IN THE IDENTIFICATION AND PREDICTION OF MECHANICAL FAILURES, Mechanical Failure Prevention Group, MFPG Interim Technical Report No. 1, Office of Naval Research, Arlington, Virginia, January 10, 1971.

Discriminant - A statistic for which a detector can be specified.

Experiment - A well-defined procedure for establishing the existence of a possible relation between a candidate for a signal and an internal condition of an equipment. An experiment must be designed so as to establish the probability of error in deciding that a signal is bona fide.

Failure - An omission of occurrence or performance. A condition characterized by the inability of a material, structure, or system to fulfill its intended purpose and resulting in its retirement from service.

Failure Detection - Implies that a failure mode has been identified, a signal has been identified, and a detection criterion has been specified.

Failure Mode - A particular manner of omission of occurrence or performance of an act or a task.

Failure Path - The path of secondary effects connecting a mechanical condition change of other components possibly terminating in equipment failure.

Hypothesis - A statement concerning the behavior of an equipment and sensor.

<u>Example</u>: The amplitude of the third harmonic of the gear-passing frequency bears no relation to gear wear.

An experiment and suitable statistical test must be devised in order to accept or reject this hypothesis at a specified confidence level.

Incipient Failure - A condition wherein the first signs of failure become apparent by acceptable means of detection.

Malfunction Path - The path of secondary effects between malfunctions of different equipment components.

Manifestation - An act which can be readily perceived by the senses.

Monitoring - The continuous observation of a diagnostic phenomenon for an indication of a change of such phenomenon reflecting a change in the mechanical condition of an equipment component.

Noise - The difference between a waveform and the signal. Noise is generated in the sensor, the transmission medium, the receiver, the filter, and the display.

Observable - Waveform, signal or signature.

Probability Detection - The probability of detecting a failure (equals 1 - P(M)).

Probability of False Alarm P (FA) - The probability of deciding that a failure is imminent or has occurred when, in fact, the equipment is not failing.

Probability of Miss P (M) - The probability of not detecting an imminent failure before or when it occurs.

Prognosis - The art or act of predicting a future condition on the basis of present signs and symptoms.

Receiver - The receiver accepts the waveform from the transmission medium, and presents it to the detector.

Secondary Effect - The effect of a mechanical condition change of one equipment component on the condition of another equipment component.

Sensor - A device used to provide an observable related to a condition of interest, e.g., a device transducing physical quantities into electrical form. A sensor does not detect.

Sensor Output Format - The form of the waveform supplied by the sensor such as analog, pulse frequency, digital.

Signal - A manifestation of an event containing information of interest.

Signature - A frequently used term usually referring to some characteristic of a waveform which is related to a condition of interest. A signature is that combination of signals indicative of some known condition of a system under test.

Sonic Analysis - Usually refers to the act of analyzing the spectral content of the sound emanating from an operating equipment.

Statistic - A characteristic of a set of observables, thought to provide a general description of the set as a whole.

Threshold Element - The element following the detector which implements a prescribed decision rule.

Transmission Medium - The medium by which the sensor output waveform is conveyed to the receiver, or by which the physical observable is conveyed to the sensor.

Trend Analysis - A means to determine if a signal is changing in some predictable manner, such as increasing in magnitude with respect to time.

Waveform - Usually a voltage-time record of a sensor output. A waveform may or may not contain a signal. A signal must be carefully described and identified. A signal is related to a failure which is impending or has occurred. The definition of that which constitutes a failure must be carefully identified before a signal can be identified.

APPENDIX III
DATA ON OSU SUPPLEMENTARY TAPES

Data was dubbed from the Hamilton-Standard AIDAPS data tapes onto 1/2-inch magnetic recording tape. The dubbed data has the advantage of being much more compact (consisting of two 10-1/2-inch-diameter, 1/2-inch-wide reels of tape) than the original data (which was contained on approximately twelve 10-1/2-inch-diameter, 1-inch-wide reels). Of course, the dubbed tape also contains much less data.

There are six tracks of the OSU tapes which contain data. These include a voice track, which serves to identify records, the transmission tachometer signal, and the following parameters: Parameter 61, the accelerometer located at the 42° gearbox output grill; parameter 123, the velocity pickup located on the upper mast of the main transmission; parameter 125, the accelerometer located at the input quill of the main transmission; and parameter 126, the accelerometer located at the tail rotor output of the main transmission.

The data includes eight runs in which no bad parts were implanted; this provides baseline data. A total of 11 runs in which bad parts were implanted are on the tape, including three runs from "Phase D" flight testing and all eight runs from "Phase E" flight testing. All recorded data was taken from the hover flight mode.

APPENDIX IV
UH-1D HELICOPTER BEARING AND GEAR-MESH FREQUENCIES

f_{ir} = frequency caused by inner race irregularity

f_{or} = frequency caused by outer race irregularity

f_b = frequency caused by rolling contact

f_{gm} = gear-mesh frequency

Shaft or Gear	Gear or Bearing Parts Number	Frequency, Hz @ 6600 rpm Shaft	f_{ir}	f_{or}	f_b	f_{gm}
Input		110				
Quill shaft	204-040-142-1		1304	1116	704	
	204-040-346-3		975	675	275	
	204-040-269		802	518	243	
Drive bevel gear	204-040-700					3190
Driven bevel gear	204-040-701					3190
Input gear shaft	204-040-345-3	51	732	606	269	
Lower planetary set	204-040-329-1					
	204-040-108-7					1983
	204-040-331-5					
	204-040-725		476	336	161	
	204-040-135		420	380	164	
Gear shaft		64				
Upper sun						
Shaft		17				
Upper	204-040-330-1,3					
planetary set	204-040-108-7					642
	204-040-331-5					
	204-040-725		160	109	52	
	204-040-135		136	123	53	
	204-040-136		62	46	20	
Upper planet						
Gear shaft		21				
Rotor mast		5.4				
	24-040-270		82	68	29	
Main reduction						
gear shaft		51				
	204-040-271		892	754	304	
	204-040-135		1298	1172	505	
Drive spur gear	204-040-763					630

Shaft or Gear	Gear or Bearing Part Number	Frequency, Hz @ 6600 rpm				
		Shaft	f_{ir}	f_{or}	f_b	f_{gm}
Driven spur gear	204-040-762					630
Lower transmission		69				
shaft	204-040-143		507	321	148	
	204-040-310		572	395	182	
Drive band gear	204-040-103-7					1865
Driven bevel	204-040-104-13					1865
Acces., tail rotor	204-040-105					1865
Tail rotor shaft		72				
Accessory drive		72				
	204-040-310-1		594	409	189	
	204-040-143-1		527	334	153	
42° bevel drive	204-040-500-009					1936
42° bevel drive	204-040-500-010					1936
42° gearbox input		72				
Output shafts						
90° input shafts						
90° bevel drive	204-040-400-009					1075
90° bevel driven	204-040-401-007					1075
90° gearbox		28				
Output shaft						
		*(MRC)		309	242	110
		*(BOWER)		305	244	125
		**(MRC)		281	217	109
		**(BOWER)		278	217	109

*90° Bevel driven gear bearings; part number not available. Bearing is available from the two manufacturers shown; those from different manufacturers have different characteristic frequencies.

**Tail rotor bearing; part number not available. Bearing is available from the two manufacturers shown; those from different manufacturers have different characteristic frequencies.

APPENDIX V
ANALYSIS OF DATA TAPES BY SCOPE ELECTRONICS

This appendix contains a report on the analysis of the data tapes (Appendix III) by Scope Electronics Inc., a subsidiary of Scope Inc. of Reston, Virginia. The author of the report is James H. Hughen. The following material is reproduced by permission of Scope Electronics Inc.

INTRODUCTION

There is interest in developing techniques for the automatic diagnosis of faulty bearings and gears in the transmission and gearboxes of military aircraft. It is hoped that the faulty components can be accurately identified and located by means of their vibration signatures. When bearings and gears fail, the vibration levels tend to increase. The increase in level occurs at frequencies which can be related to mechanical occurrences in the bearings or gears. These fault frequencies can be predicted; however, it is difficult to detect a small change in level due to the inherent randomness of the signature. The problem in automatically diagnosing bad bearings and gears is to detect characteristic changes in the noise-like vibration signature, changes which may or may not occur at predictable discrete frequencies, but which signify the onset of degradation prior to actual catastrophic failure.

This memorandum presents the results of an experiment applying modern pattern recognition techniques to the task of identifying faulty bearings and gears. The vibration signatures were digitized and sample spectra were computed using the discrete Fourier transform (FFT). Some of the samples were presented to the classifier for training purposes and the remaining samples were withheld for evaluation. Several variations on data base and feature sets were tested. The classification accuracy achieved was consistently about 90%. This score is computed by dividing the number of samples correctly classified by the total number of samples presented to the classifier.

This score is felt to be significant for two reasons. First, in view of the preliminary nature of the experiment, it is almost certain that the best feature set for discriminating between the categories has not been found yet. Secondly, the inclusion of post-detection integration can render a raw score of 90% quite sufficient for practical operations.

A detailed discussion of the results follows. The details of the data preparation and processing are given. The conclusion is made that the pattern recognition techniques are strongly applicable to the problem of automatic diagnosis of helicopter transmission and gearbox faults.

APPROACH

DATA PREPARATION

The U. S. Army Aviation Systems Command established a test bed program for the purposes of instrumenting, recording and analyzing vibration data on a UH-1H helicopter. SCOPE Electronics obtained from Dr. Don Houser of Ohio State University two analog tapes containing vibration recordings made on this program.

TABLE VIII. VIBRATION MEASUREMENTS

Sensor	Transducer	Parameter
61	Accelerometer	Gearmesh - 42° gearbox
123	Velocimeter	Main mast bearing - radial
125	Accelerometer	Input quill gearmesh
126	Accelerometer	Tail rotor quill gearmesh

The four sensors used on the recordings are listed in Table VIII. Several runs (see Table IX) provided example signatures for baseline and various fault conditions.

The frequency range of these recordings was from dc to about 2.5 kHz*. The data were further low-pass filtered to 2.5 kHz and sampled into an A/D converter at 6 kHz. Records of 1/3-second duration were made, providing a frequency resolution of 3 Hz and a record length of 2048 sample points. A sample spectrum of 1024 points was computed from each record.

In view of the limited time available for this experiment, it was decided to conduct a thorough experiment on a single sensor. Since more of the fault runs corresponded to the 42° gearbox, sensor 61 was the logical choice.

Three data bases were made up, each data base consisting of an equal number of samples from the baseline runs and from the failure runs. To compromise between data base size and spectral estimate quality, each sample in the data base was generated by averaging four or eight sample spectra corresponding to the 1/3-second record. If a spectral estimate is consistent in a statistical sense, then averaging together enough samples will produce a result arbitrarily close to the true spectrum. However, if the underlying random process is not stationary, then the estimate produced

*The original frequency range was from dc to 5 kHz, but the original recordings had been copied at half speed.

TABLE IX. VIBRATION DATA			
Item	Run	Type	Failure
1	D-126	baseline	
2	D-130	baseline	
3	D-171	baseline	
4	D-174	baseline	
5	D-177	baseline	
6	D-180	baseline	
7	D-183	baseline	
8	D-188	baseline	
9	D-162	1 failure	tail rotor quill bearing
10	D-165	1 failure	input quill bearing
11	D-159	1 failure	main transmission bearing
12	E-1	2 failures	main and 42° gearboxes
13	E-2	2 failures	main and 42° gearboxes
14	E-3	3 failures	main, 42°, and 90° gearboxes
15	E-4	3 failures	main, 42°, and 90° gearboxes
16	E-5	2 failures	42° and 90° gearboxes
17	E-6	2 failures	42° and 90° gearboxes
18	E-7	1 failure	90° gearbox
19	E-8	1 failure	90° gearbox

by averaging together independent samples will at some point become degraded rather than enhanced. In other words, there is a proper number of samples which can be averaged together for the best results. On the other hand, the classification scheme used in this experiment requires that some distribution parameters be estimated, specifically the means and covariances of an assumed multivariate Gaussian distribution. Since the sample mean is not a sufficient statistic for covariance, a better covariance estimate would be obtained with the larger number of unaveraged samples. Also, to evaluate the classifier, the larger data base would produce a statistically more significant result.

In order to average sample spectra, the individual samples have to be carefully synchronized. A speed variation in the helicopter power train causes a scale change in the spectrum and not simply a frequency shift. The scale factor in the 42° gearbox vibration spectrum can be found by dividing the actual gearmesh frequency f_g by the reference gearmesh frequency, say, f_r; e.g., f_r = 1936 Hz at 6600 rpm. It is a simple matter then to rescale the sample by dividing the frequency corresponding to each cell by the scale factor f_g/f_r.

FEATURE SELECTION

Feature selection is perhaps the key step to a successful solution in a pattern recognition problem. In a signature classification problem, the

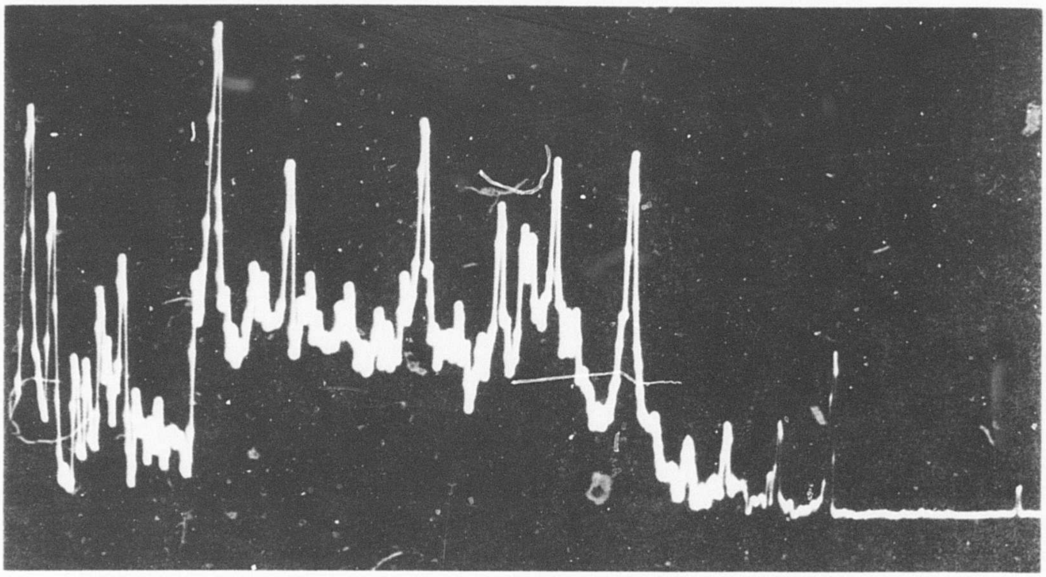
dimensionality of the measurement space is usually quite high. The goal of feature selection is to drastically reduce the dimensionality of the data vector presented to the classifier in the interest of economy and simplicity of classifier design, while at the same time maintaining the classification performance above some minimum acceptable level.

A valuable tool to assist in the feature selection task has been developed by Dr. J. W. Bessman and Mr. J. W. Glenn of SCOPE Electronics Inc.[75,76] Dr. Bessman's algorithm known as OP-SEEKER is based on an information theoretic approach; the algorithm evaluates an information statistic, $I(X/Y_n)$, approximately the information contained in the feature subset Y_n (consisting of n features) about the information source. The algorithm first ranks the features by computing the information statistic for each feature one at a time. Then feature subsets of size n (n = 1,2,...20) are found such that the information statistic is maximized for each value of n. For computational reasons, these subsets are constrained so that each higher order subset contains the lower order subsets. Within the limitations imposed by the constraint and computational approximations, the OP-SEEKER algorithm finds the best subset of features from a given vector.

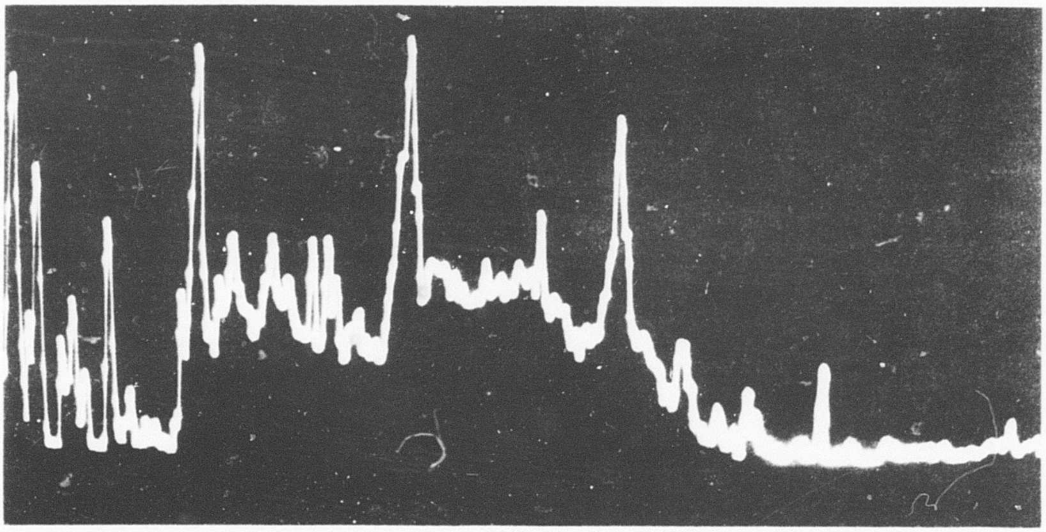
Two feature sets consisting of twenty features each were constructed. A preliminary examination of the spectra was of little benefit in picking features. (See Figs. 88 and 89.) As a first effort, it seemed reasonable to discriminate between good and failure by using only those predictable fault frequencies associated with the two types of bearings in the 42° gearbox as well as the gearmesh frequency and shaft ratio lines in the upper and lower sidebands associated with the gearmesh and harmonics of the gearmesh. The twenty features were chosen to cover failures in both bearings and gears. The second feature set included four wide-band sections of the spectrum and two ratios of these sections in addition to some predicted bearing fault frequencies and several gear frequencies. The two feature sets are listed in Table X and Table XI according to their information content as computed by the OP-SEEKER algorithm.

CLASSIFIER

The classification algorithm used in this experiment is based on a Bayes solution (minimization of the average value of some loss function). The *a priori* probabilities of each class are assumed to be equal, and the loss function is chosen so that the Bayes classifier is specified by maximization of the probability density function (likelihood) of the measurement vector conditioned on a given signature class. Several advantages accrue to this approach, the main one being that the discriminant functions are completely specified in terms of the parameters of the underlying distribution. Hence, there is no need for training in the usual sense (of learning the coefficients of the discriminant functions based on some assumed discriminant function structure). There is, however, the requirement for estimating the parameters of the distribution. Such a classifier will perform very well when the underlying distribution is known exactly, but when the measurement vectors do not come from the assumed distribution,



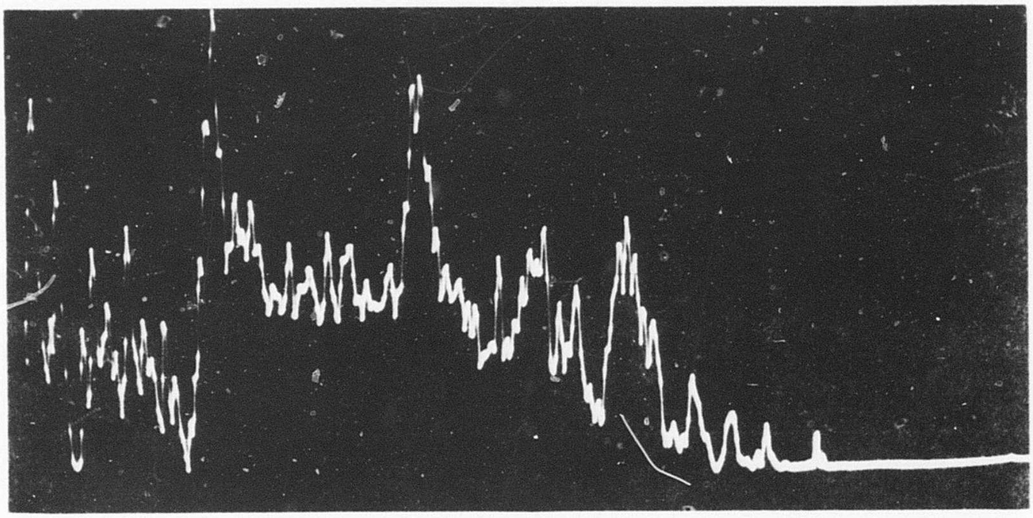
A



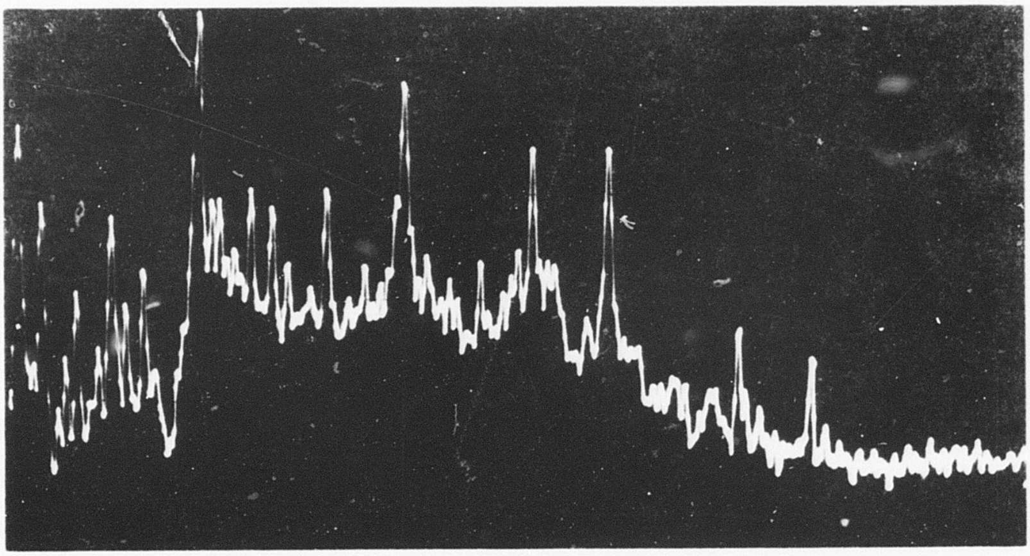
Horizontal Scale: Amplitude
Vertical Scale: Frequency

B

Figure 88. Vibration Spectra Exhibiting Baseline Conditions in the 42° Gearbox. Sensor No. 61. A is Run 130; B is Run 183.
Frequency Scale : 0-5 kHz, Rsolution
Resolution: 15 Hz
No. of Ensembles Averaged = 16



A



B

Horizontal Scale: Amplitude
Vertical Scale: Frequency

Figure 89. Vibration Spectra Exhibiting Failures in the 42° Gearbox.
Sensor No. 61. A is Run E-2. B is Run E-4.
Frequency Scale: 0-5 kHz
Resolution: 15 Hz
No. of Ensembles Averaged = 16

TABLE X. FEATURE SET NUMBER 1
(RANKING BY OP-SEEKER)

Feature Number	Rank	Frequency	Description
12	1	94.5	f_b, single bearing
2	2	1004	first USB line, 42° gear mesh
9	3	76.5	f_b, double bearing
17	4	409	second harmonic of f_o, single bearing
14	5	334	second harmonic of f_o, double bearing
13	6	527	second harmonic of f_i, double bearing
20	7	597	adjacent cell to second harmonic of f_i, single bearing
3	8	932	first LSB line, 42° gear mesh
5	9	1972	first USB line of second harmonic, 42° gear mesh
15	10	153	second harmonic of f_b, double bearing
19	11	192	adjacent cell to second harmonic of f_o, single bearing
6	12	1900	first LSB line of second harmonic of 42° gear mesh
8	13	167	f_o, double bearing
10	14	297	f_i, single bearing
11	15	204.5	f_o, single bearing
18	16	189	second harmonic of f_o, single bearing
1	17	968	42° gear mesh
16	18	594	second harmonic of f_i, single bearing
4	19	1936	second harmonic of 42° gear mesh
7	20	263.5	f_i, double bearing

TABLE XI. FEATURE SET NUMBER 2
(RANKING BY OP-SEEKER)

Feature Number	Rank	Frequency	Description
2	1	1004	first USB line, 42° gear mesh
18	2	700-850	
9	3	1972	first USB line, second harmonic, 42° gear mesh
8	4	932	first LSB line, 42° gear mesh
12	5	1900	first LSB line, second harmonic, 42° gear mesh
1	6	94.5	f_b single bearing
15	7	1200-1350	
17	8	ratio 15/16	
16	9	2300-2500	
6	10	527	second harmonic, f_i, double bearing
11	11	192	adjacent cell to second harmonic, 42° gear mesh
20	12	ratio 19/18	
5	13	334	second harmonic, f_o, double bearing
10	14	297	f_i, single bearing
14	15	297	included twice (unintentionally)
13	16	167	f_o, double bearing
7	17	597	adjacent cell to second harmonic, f_i, single bearing
19	18	650-700	
4	19	409	second harmonic, f_o, single bearing
3	20	76.5	f_b, double bearing

the classification accuracy will suffer accordingly. (Reference 77 contains an excellent exposition of the principles of pattern recognition.)

When the conditional probability densities are assumed to be normal or Gaussian, the resulting discriminant function is a quadratic form which depends on the mean vector and the covariance matrix (of the conditional density). The procedure used in this experiment was to estimate the mean and covariance using the training data base, then to classify the training samples, and finally to verify the classification performance using evaluation samples.

RESULTS

Table XII summarizes the results obtained in this experiment. Even though the summary lists four separate experiments, each successive experiment was a logical modification of the previous one. Initially, eight spectra were averaged to obtain a single sample. Since the resulting data base was small, all the samples were used to estimate the distribution parameters, i.e., to "train." Usually, the evaluation score will be within 5% of the training score; and indeed, to have high confidence in the results, fairly close agreement between train and evaluation scores is essential. Figure 90 shows the classification accuracy as a function of the number of features utilized. For the first experiment, a classification accuracy of 87.5% was obtained with 19 features.

Having too small a data base to permit an independent evaluation is a deficiency; hence, a larger data base was sought. Since only a limited amount of data was available, four sample spectra were averaged instead of eight. This would, of course, have produced a data base of twice the original size. However, there had been a larger number of classification errors in run E-1; hence, this run was eliminated from the second data base. Using all 66 samples per class for training, the classification accuracy reached 92.4%. Training on half the samples, the scores were 89.5% on training samples and 91% of evaluation samples.

This performance was not discouraging, but after some reflection, it appeared that a further experiment should be performed with the following modifications. First, put back the samples from run E-1; second, instead of training on samples chosen randomly, choose training samples and evaluation samples from non-overlapping portions of a run; third, try normalizing each sample; fourth, include some wideband features since 100% classification has not been achieved with the discrete frequency features. Data base number three and feature set number two were generated incorporating these changes. The classification performance achieved with this fourth experiment was 90% on the training samples and 87.5% on the evaluation samples. Again, half the samples were used for training. The results of this experiment are rather encouraging because 12 of 18 total errors occurred in run E-1. In fact, every sample in this failure run was classified as good. The six remaining errors were scattered throughout the data base and hence could all be eliminated by some simple

TABLE XII. CLASSIFICATION SUMMARY

Experiment	Data Base	Feature Set	Samples Total	Samples Train	Results Train	Results Eval.	Comments
1	1	1	40	40	87.5%	-	8 spectra averaged to produce 1 sample; data base too small for evaluation; samples are not normalized
2	2	1	66	66	92.4%	-	4 spectra averaged to produce 1 sample; unnormalized samples
3	2	1	66	33	89.5%	91	4 spectra averaged to produce 1 sample; unnormalized samples
4	3	2	80	40	90%	87.5	4 spectra averaged to produce 1 sample; each sample is normalized 12 of 12 E-1 samples misclassified; PDI would eliminate all other errors

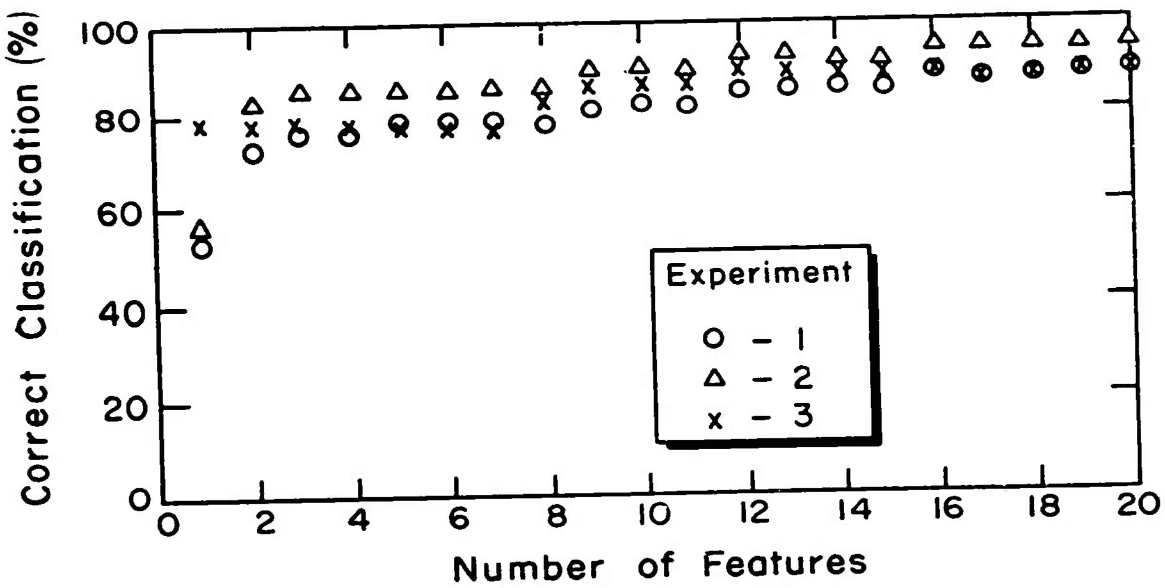


Figure 90. Percentage of Correct Classification vs. Number of Features.

post-decision integration scheme, such as requiring three sequential decisions to agree before making a final decision. If this or some similar scheme is used so that one decision is made for each run, then 11 of the 12 runs in the fourth experiment are correctly classified.

CONCLUSIONS

A classification score of 100% would, of course, have been desirable. However, the 90% score is based on a decision for each vibration sample presented to the classifier. In actual operations this would be unnecessary as well as undesirable, and as the result of the fourth experiment indicated, post-decision integration can improve the classification accuracy dramatically. In fact, it is conceivable that a raw score of 90% can be equivalent to virtually 100% with the inclusion of post-decision integration.

The raw score of 90% could be indicative of either of the following:

The vibration spectra do not contain enough information for 100% separation.

The appropriate features have not been found.

If the latter speculation is true, then pattern recognition techniques are even more strongly warranted. In all likelihood, pattern recognition can accommodate a high dimensional feature vector more efficiently than some intuitive approach. The search for the best feature vector in this writer's opinion will be expedited by combining a knowledge of the underlying physical model with the methods of pattern recognition.

There are many advantages of pattern recognition techniques over ad hoc techniques. It is well-known that when underlying probability distributions are known, a decision theoretic approach provides the optimum decision strategy in the sense of minimizing some expected loss function. When the underlying distributions are known, parametric pattern recognition theory coincides with decision theory, but when the underlying distributions are unknown, pattern recognition techniques are tantamount to an approximate decision theoretic approach. This is not to say that pattern recognition always provides the most powerful classification technique, but there is no known technique which is generally more powerful.

One natural advantage of pattern recognition over many intuitive approaches is the ease with which pattern recognition can be automated. The mathematical manipulations can be readily accomplished digitally, which means that not only general-purpose computers but minicomputers or special-purpose digital logic circuits can provide the necessary implementation.

One may be reluctant to conclude that the applicability of pattern recognition to the vibration analysis problem has been conclusively

demonstrated; however, in view of the preliminary nature of the experiment, the results obtained are sufficient justification for optimism.

One deficiency in the experiment is that the training samples and the evaluation samples were derived from the same vibration runs. Perhaps there are other deficiencies which have escaped the attention of the experimenter, but these deficienceis are not to the discredit of pattern recognition methods per se. Neither are they a serious discredit to this experiment, which was conducted under some rather severe constraints. This experiment was intended to demonstrate the application of pattern recognition to vibration analysis. It is felt that this objective was accomplished, and in the course of so doing, this experimenter became very convinced of the appropriateness of the application.

APPENDIX VI
QUANTITATIVE RANKING SYSTEM

During this program it was desired to produce a method which would allow a quantitative, i.e., numerical, ranking to be evaluated for the various diagnostic systems. This appendix describes the procedure which was arrived at.

SYSTEM RATING TECHNIQUE

The set of questions in this listing is designed to provide a quantitative manner of rating diagnostic schemes. Each question is assigned a certain number of points for a yes or no answer. For example, 15N would signify 15 points for a no answer and 0 point for a yes answer. If the answer is neither completely positive nor completely negative, some number of points between 0 and the maximum could be assigned. The maximum number of points possible for a "perfect" system with this rating scheme is 425. The techniques are given a percentage rating with respect to 425, with 100% designating the "perfect" system.

The first set of questions deals with discriminant ability, i.e., how well does the system detect failures and what information must be provided to implement the diagnostic scheme. Question I-A determines how finely the technique can determine failures, i.e., per L.R.U., per individual component of an L.R.U., or per failure mode of an individual component. And, of course, if a technique can distinguish a failure mode, it can also detect the component and L.R.U. that the failure occurs in. Partial credit may be given if the system can distinguish between some failure modes but not all, e.g., between general wear and discrete faults. Finally, it asks if the system can provide an indication of whether a failure is becoming progressively worse, i.e., is there a sensitivity to the degree of failure.

Question I-B questions the need to provide limit values to trigger the system. By limit value is meant a numerical value which indicates a failure, e.g., overall vibration level, a ratio of various signals, signal-to-noise, etc. Then the manner in which limits may be arrived at is questioned, i.e., on a test stand or in situ.

A set of baseline questions comes next. By baselines are meant larger pieces of information about system characteristics, e.g., spectra or amplitude levels at various operating conditions. This is in opposition to the individual numerical limits mentioned previously. First, the need for "good" baselines is questioned, where "good" refers to baselines which are used as starting points or references on a system without any failures. Deviation from "good" baselines could signify a failure. The next determination is the level at which a "good" baseline must be developed, i.e., vehicle class or individual vehicle. And, finally, whether or not a test stand is adequate for developing a "good" baseline is asked.

The next several questions discuss the need for "bad" baselines, i.e.,

whether baselines must be developed for failed parts to use a technique. First, a determination is made of whether implants are required on an L.R.U., individual component, or individual failure mode basis. Then, whether or not a test stand can be used for developing "bad" baselines is asked.

The next four questions discuss the effects of load and speed changes on the technique's results. First, the question of whether the system is load and/or speed sensitive is asked; and then, the question is asked whether load and/or speed can be normalized out of the results in any way.

The final question in this section has to do with the effect of noise on the system results. Noise is interpreted as any signal which might arise from a part of the vehicle other than the one being specifically monitored. The question asks if these outside signals can interfere with the operation of the diagnostic technique.

The second set of questions has to do with the transducers required for implementation of the diagnostic technique. Question II-A looks at the number of transducers required. The questions asked are: can one transducer per L.R.U. produce the results, must several transducers per L.R.U. be required, or, finally, must each component (gear, bearing, etc.) require its own transducer?

Question II-B questions the type of transducer which is required. First, it asks whether or not special signal conditioning other than simple amplification is needed. Secondly, it questions the need for a dynamic range other than standard (0 - 10 kHz). Finally, it asks whether special durability considerations are required. By this it determines whether the transducer must be placed in a position of high temperature, stress, pressure, etc., that would require a special design.

Question II-C discusses the location that each transducer must occupy to make the technique work. A determination is made of whether a transducer must be actually located on the helicopter, whether it must be mounted on the L.R.U., or whether it must be mounted on an individual bearing race, shaft mount, etc. It then questions the need for the transducer to be built in, i.e., not removable from its mounted position. The next question is whether mounting position is easily accessible, i.e., whether a major tear-down of the transmission is needed to locate or remove transducers. Finally, Question II-C6 is whether the transducer location is such that it picks up significant cross-talk between different components or L.R.U.'s. This might cause the results to be influenced by a component other than the one being monitored.

The third major grouping of questions is concerned with the processing hardware required for operation of a technique. It first questions where the equipment must be used, i.e., whether a test may be run on the ground or done on-board the helicopter. Then it asks whether the system could detect failures in test stand runs. This could determine whether a given L.R.U. has undergone an adequate overhaul or requires an overhaul after removal from a helicopter. The next question discusses the need of actual

flight tests versus hover tests or ground run-ups, thereby determining whether a cable could be connected to instrumentation on the ground or if all data acquisition and analysis gear must be flown on the helicopter. Finally, it asks whether monitoring must be continuous or whether periodic tests are usable.

The next question is whether special personnel are required for system operation. Highly trained people might be needed if system operation required sophisticated calibration or installation procedures. Question III-C questions the weight of the system, with anything over 10 pounds being considered heavy if it must be flown with the aircraft.

Question III-D discusses the type of processing required. It first asks whether on-line processing is required as opposed to taping, storing, and then processing the data. Then it determines the need for continuous processing versus batch or periodic processing. Finally, it questions the need of a nonportable digital computer. This is based on whether memory requirements are such that a permanent computer installation must be required.

The fourth major set of questions is concerned with the type of output that is available from the system. First Go/No-Go signals are discussed. By Go/No-Go is meant some type of alarm signal. To provide this type of signal, the system must be able to discern automatically whether or not a failure is present. Then the availability of such a signal at the L.R.U. level or at the component level is questioned.

Question IV-B asks whether there is a dead-time between data gathering and the presentation of results. This question is concerned with the amount of processing required and whether the technique can operate in real time or not. Next, IV-C questions the need for operator interpretation. The desire is to know whether trending or other mathematical analysis must be performed by a highly trained specialist rather than automatically. Finally, Question IV-D asks whether the data used by the technique is available for further, possibly more sophisticated, analysis rather than being destroyed in the analysis procedure.

It is noted that throughout the set of questions some redundancy occurs. It is felt that this was required in some sense to fully provide answers to all of the questions that are needed to describe a diagnostic technique in the most complete manner.

RATING TECHNIQUE QUESTIONS

I. Discriminant Ability
   A. Degree of the ability to discriminate between "good" and "bad" systems.
      1. Can failures be detected on an L.R.U. basis? (50 Y)
      2. Can failures be detected on an individual component basis (quill bearing, sun gear, etc.)? (25 Y)

3. Can the type of failure mode be detected (pit, spall, wear, etc.)? (15 Y)
4. Does the technique have any sensitivity to the degree of failure experienced? (6 Y)

B. System triggering limit values.
1. Must limits be established for each component as a class? (10 N)
2. May limit values be established in a test stand? (10 Y)
3. Must limit values be established in situ? (10 N)

C. Baseline signatures.
1. Are "good" baseline signatures required? (10 N)
2. Must baselines be provided by vehicle class (UH-1, CH-47, etc.)? (5 N)
3. Must baselines be provided for each vehicle? (5 N)
4. Is test stand data adequate for developing "good" baselines? (5 Y)
5. Are failure implant signature baselines required? (15 N)
6. Are they required on an L.R.U. basis? (10 N)
7. Are they required on a component basis? (10 N)
8. Are they required for specific individual failure modes? (10 N)
9. Is test stand data adequate for developing failure signature baselines? (5 Y)

D. Load and speed effects.
1. Is the technique load sensitive? (5 N)
2. Can load be normalized? (5 Y)
3. Is the technique speed sensitive? (10 N)
4. Can speed be normalized? (5 Y)

E. Is the system susceptible to noise problems? (15 N)

II. Transducers

A. Number
1. Can one transducer per L.R.U. work? (15 Y)
2. Can several transducers per L.R.U. work? (10 Y)
3. Must each component have an individual transducer? (5 N)

B. Type
1. Is special signal conditioning required? (4 N)
2. Is a special dynamic range required (other than standard)? (4 N)
3. Does the technique require special durability considerations (high temperature, pressure, etc.)? (4 N)

C. Location
1. Must the transducer be located on the helicopter? (10 N)
2. Must the transducer be located on the L.R.U. casing? (5 N)
3. Must the transducer be located on an individual component (bearing race, etc.)? (10 N)
4. Must the transducer be built in, i.e., not removable from mounting position? (10 N)
5. Is the transducer position easily accessible? (5 Y)
6. Does the transducer pick up significant cross-talk from components other than the one it is monitoring? (5 N)

III. Processing hardware

A. Ground based vs. on-board.

1. Can failures be detected in test-stand runs? (5 Y)
2. Can failures be detected in ground run-ups or hover tests? (5 Y)
3. Must actual flight data be used? (5 N)
4. Must special equipment be carried for flight testing? (5N)
5. Must monitoring be continuous? (5 N)

B. Are highly trained personnel required for system operation? (6 N)

C. Is weight a constraint, i.e., does the system weigh more than 10 pounds? (6 N)

D. Processing
1. Is on-line processing required? (6 N)
2. Must processing be continuous? (6 N)
3. Is a nonportable digital computer required for processing? (6 N)

IV. Output presentation.

A. Go/No-Go
1. Is a Go/No-Go signal available? (10 Y)
2. Is it available at the L.R.U. level? (4 Y)
3. Is it available at a component level? (4 Y)

B. Is there a dead time between data gathering and presentation of results? (9 N)

C. Is operator interpretation of results required? (9 N)

D. Is data available for further analysis if desired? (6 Y)

RATING OF DIAGNOSTIC SYSTEMS

By applying the rating technique questions to a diagnostic system, a numerical evaluation of this system can be determined. There are actually two numerical ratings which are of interest, the overall score and the score on the Discriminant Ability questions. By comparing the overall scores of different systems, a relative ranking as to overall system capabilities may be arrived at. The score on the Discriminant Ability section is an indication of the possible future development capability of a technique. This would allow consideration of techniques which have a sound discrimination basis but which have not reached a very high level of sophistication in system development.